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Tavana, M., Liu, W., Elmore, P., Petry, F. E., & Bourgeois, B. S. (2016). A practical taxonomy of methods and literature for managing uncertain spatial data in geographic information systems. Measurement, 81, 123-162. DOI: 10.1016/j.measurement.2015.12.007

Published in:
Measurement

Document Version:
Publisher's PDF, also known as Version of record

Measurement 81 (2016) 123–162

Contents lists available at ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement

A practical taxonomy of methods and literature for managing uncertain spatial data in geographic information systems

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A R T I C L E I N F O

Article history:
Received 3 November 2015
Received in revised form 14 November 2015
Accepted 4 December 2015
Available online 14 December 2015

Keywords:
Uncertainty
Spatial data
Geographic information systems
Taxonomy
Literature review

A B S T R A C T

Perfect information is seldom available to man or machines due to uncertainties inherent in real world problems. Uncertainties in geographic information systems (GIS) stem from either vague/ambiguous or imprecise/inaccurate/incomplete information and it is necessary for GIS to develop tools and techniques to manage these uncertainties. There is a widespread agreement in the GIS community that although GIS has the potential to support a wide range of spatial data analysis problems, this potential is often hindered by the lack of consistency and uniformity. Uncertainties come in many shapes and forms, and processing uncertain spatial data requires a practical taxonomy to aid decision makers in choosing the most suitable data modeling and analysis method. In this paper, we: (1) review important developments in handling uncertainties when working with spatial data and GIS applications; (2) propose a taxonomy of models for dealing with uncertainties in GIS; and (3) identify current challenges and future research directions in spatial data analysis and GIS for managing uncertainties.

1. Introduction

The modern geospatial revolution enhanced by geographic information systems (GIS) has greatly increased the understanding of our physical environment. The basic components of GIS include [26]: (1) a data input component for collecting and processing spatial data; (2) a data storage and retrieval component for organizing spatial data; (3) a data manipulation and analysis component for changing spatial data; and (4) a data reporting component for displaying spatial data. Spatial data are not always precise and uncertainty in geographical data is widely accepted due to the way the world is perceived, measured, and represented [51]. Varsi [40,41] has observed that vagueness is a major factor in geographical information representation since concepts such a river's length or a mountain's height in a specific area are uncertain as the specification of a river or peak are vague concepts. Baofu [2, p. 297] states "all geographical data are inherently inaccurate, and these inaccuracies will propagate through GIS operations in ways that are difficult to predict." Couclelis [10] further describes uncertainty as an inherent property of complex geospatial knowledge that must be managed effectively. Many of the problems associated with the accurate measurement of spatial databases and GIS are also prevalent in all types of database systems. Uncertainty

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URL: http://tavana.us/ (M. Tavana).

http://dx.doi.org/10.1016/j.measurement.2015.12.007
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in many of these systems is not simply an error or flaw to be reduced or eliminated but an important component of the system that must be taken into consideration. Therefore, uncertainty plays a critical role in the analysis of spatial data and GIS which contain descriptive as well as positional data. The uncertainty can be represented by a wide range of values that may include the actual measurement of the object as only one point. Fig. 1 illustrates the complexity that can be observed in a real-world example. This figure is an image of the Louisiana gulf coastal region in the area of the Atchafalaya Bay and illustrates the difficulty of specifying the characteristics of the spatial features. The boundary between the coastline and the Gulf of Mexico, the relationship of the various waterways and their characterization are difficult to specify as they exhibit both spatial and temporal uncertainty.

The remainder of this paper is organized as follows. In Section 2, we present a review of the statistical and non-statistical methods used for managing uncertain spatial data in GIS. More specifically, we review fuzzy set/possibility theory and rough set theory used for managing vague/ambiguous data and probability theory and Dempster–Shafer (D–S) theory for managing imprecise/inaccurate/incomplete spatial data. In Section 3, we discuss our study and results and in Section 4, we draw our conclusions and outline future research directions.

2. Managing uncertainties in spatial data

In this section, we examine some practical approaches used to represent various aspects of geospatial data. Uncertainty can refer to vagueness, ambiguity, imprecision, inaccuracy, incompleteness, or anything that is undetermined. In this study, we refer to "vagueness" as the inability to clearly understand the meaning of a word or phrase; "ambiguity" as multiple meanings in a word or phrase; "imprecision" as the level of variation associated with a set of measurements; "inaccuracy" as a situation where the assessment fails to give the true measurement; and "incompleteness" as the lack of relevant measurement.

A wide range of statistical and non-statistical methods have been proposed in the literature to model uncertainties in spatial data. In this study, we present a practical taxonomy of these methods by grouping them into two general categories: statistical and non-statistical methods. As shown in Fig. 2, statistical methods are often used to model imprecise, inaccurate, or incomplete spatial data while non-statistical methods are used to handle vague or ambiguous spatial data. Probability theory and D–S theory are the most widely used statistical methods for modeling uncertain spatial data while fuzzy set/possibility theory and rough set theory are the most commonly used non-statistical methods for managing uncertainties in spatial data modeling.

2.1. Statistical approaches

In this study, we identified 42 papers which applied D–S theory in a GIS environment. Malpica et al. [25] present a survey of (D–S) theory in GIS. Here we discuss how probability and D–S theory have been used to represent geospatial data with uncertainty.

The D–S theory of evidence (also referred to as the *belief function theory* or *evidential reasoning theory*) is general framework formalized by Shafer [35] for representing and reasoning with uncertain, imprecise, or incomplete information. Shafer's seminal book was based on Dempster's original idea [13] on the modeling of uncertainty in terms of upper- and lower-probabilities induced by a multivalued mapping [22]. The key concept in D–S theory is that an amount of probability mass (a value in $[0,1]$) can be assigned to a subset of a set of solutions to a question (such as all the possible values of size of a particular space) rather than just a singleton set, as in the case of probability

Fig. 1. Gulf of Mexico coastal region: Atchafalaya Bay area.

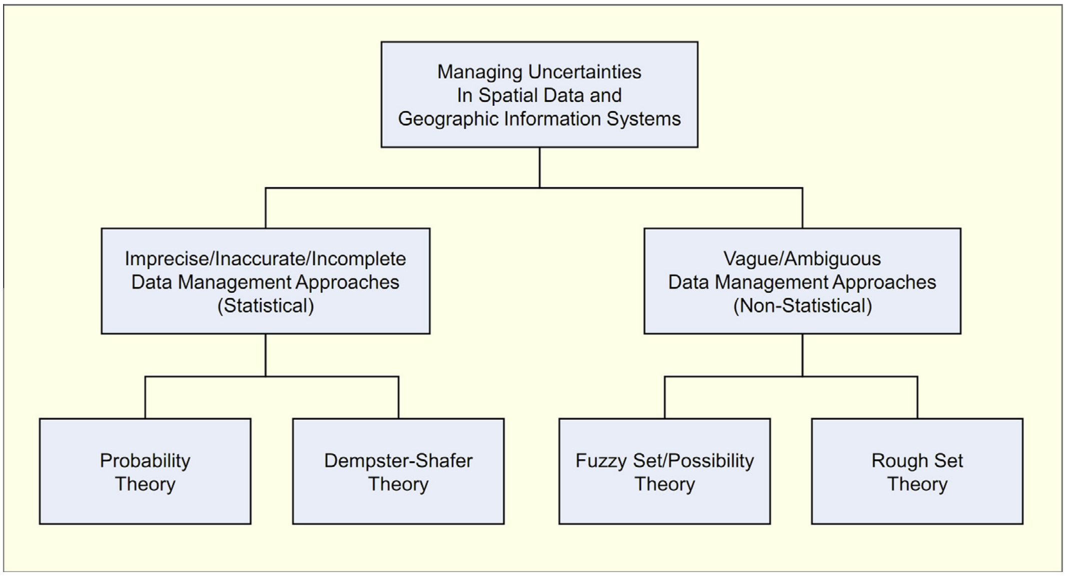

Fig. 2. A practical taxonomy of methods used for managing uncertainties in GIS.

theory. When all the subsets bearing probability masses are singleton sets, D–S theory is reduced to standard Bayesian (probabilistic) reasoning. *We should note that D–S theory is a generalization of Bayesian theory and does not compete with or replace Bayesian approaches.* D–S theory has been widely used to medical and sensor information modeling and aggregation (e.g., [23,38]. Yager et al. [46] contains most of the significant works in D–S theory at the time.

There are two main interpretations of what a probability mass assigned to a subset means [19], for example, assigning 0.6 to subset {Edinburgh, Belfast} to a question: "where person A lives now?" and assigning the remaining 0.4 to the whole set of all possible cities A may live. The first interpretation views D–S theory as an extension of probability theory. With this view, when a probability distribution is propagated from one set of elements to another related set through a mapping, it is not possible to generate a probability distribution on the latter set, instead, it generates a new function which could assign probability mass values to subsets. Shafer's original work would very much follow this vine. The second interpretation views D–S theory as a new theory to model an intelligent agent's information (or knowledge), independent of probability theory. Smets' work, especially the transferable belief model [36], would be a typical example of such interpretation. Therefore, with the first view, assigning 0.6 to subset {Edinburgh, Belfast} can be interpreted as that from some probability evidence gathered on some relevant possible worlds, there is probability mass 0.6 supporting the hypothesis that person A lives in one of these two cities, but we do not know which one. With the second view, an agent subjectively *assumed* that person A lives in one of the two cities probably 0.6, without relating it to any probability evidence.

Largely due to the ability to assign probability masses to subsets of possible worlds, D–S theory has the ability to easily model ignorance in information. For instance, value 0.4 to the whole set of possible values to a questions suggests the agent has no knowledge as how to allocate this value to any subsets. Value 0.6 assigned to subset {Edinburgh, Belfast} also means that an agent does not have any further information as how to allocate a proportion of 0.6 to either of the two cities. If 0.3 is assigned to each of the cities, like what would have been done in probability theory, then *equal probably* assumption would have been assumed and applied, which the agent may not wish to impose upon. This is the first advantage of D–S theory.

Information or evidence may come from different sources. When this happens, a fusion process (or combination, aggregation) shall be in place to combine information from these sources to generate a consensus view of what all these pieces of evidence tell an agent. Dempster's combination rule has the ability to combine pieces of evidence from distinct sources. Because this rule is both commutative and associative, it can be applied to combine pairs of evidence until all evidence has been considered. This rule has been widely applied (as one of the main attractions of applying D–S theory) in many real-world applications. This is the second advantage of D–S theory.

With these two advantages, the former allows an agent to describe ignorance because of lacking information, and the latter allows an agent to narrow down the possible solution space as more evidence is accumulated. D–S theory not only has a close connection with probability theory (when it is viewed as an extension of probability theory), it also takes possibility theory as its special case (described later). Essentially any possibility distribution (a basic concept to model evidence), can be transformed into a form of basic probability assignment (also called mass functions).

Even though D–S theory has been widely applied in real-world problems, it has been criticized for producing counterintuitive results in some cases when applying Dempster's combination rule [50], especially when evidence contradicts each other. Therefore, a number of alternative combination rules have been proposed to overcome the limitations of Dempster's combination rule. Nevertheless, it is proved that there does not exist a *perfect* combination rule, if a set of rational properties shall be possessed by such a rule [15]. Another issue when considering how to combine evidence is to deal with inconsistency (or conflict) among evidence. When two pieces of evidence do not agree with each other, such as one evidence assigns 0.6 to {Edinburgh, Belfast}, another assign 0.1 to the same subset, how can an agent quantify the degree of conflict? In recent years, there has been a considerable amount of research on defining conflict between evidence [21], and conflict within a single piece of evidence. A comprehensive survey of different measures for assessing degrees of conflict is presented by Jousselme and Maupin [20]. An additional criticism is the computational expense. As we will discuss below, D–S computations can scale exponentially. Practitioners often have to look for sparsity or approximations to reduce computational complexity.

2.1.1. Basic concepts in D–S theory

In our discussions below, we will use two simple running examples to illustrate key definitions in D–S theory

Example 1 – Police suspect pursuit:

A police force is attempting to apprehend a criminal suspect. There is evidence provided to the police that the criminal may be in a geospatial area A (which could be a building, a block of a city or town, a section of a forest, or etc.). The detective in charge of the case considers eyewitness reports, psychological profiles of the suspect, geographic characteristics of area A, etc. The detective thinks that the suspect is hiding in A at least 40% of the time, and will not be in area A, notated as $\overline{A}$, at least 20% of the time. The detective, however, is unsure about the suspect's presence for the remaining 40% of the time.

Example 2 – Balls in an urn with incomplete information:

Consider a collection of balls in an urn that consists of three shades: white, gray or black. In a two-person experiment, Experimenter A draws balls from the urn without replacement. This person gives verbal information to Experimenter B regarding what ball was drawn. Experimenter B tallies the draw results, but does not see what is drawn. This person must rely strictly on the verbal information. Now, Experimenter A is always truthful, and will sometimes report "white," "gray" or "black"; however, Experimenter A sometimes says, "not white," which means the ball could be either gray or black. Likewise, Experimenter A also says for some of the results "not gray," "not black," or "I drew a ball." The later result means that the ball could be any of the three shades. Hence, while Experimenter A is always truthful, sometimes the information is incomplete.

With these two examples, we now review key definition as discussed in Shafer [35]. In D–S theory, a piece of information is usually described as a mass function on a frame of discernment.

Definition 1 (*Frame of Discernment*). A set is called a frame of discernment (or simply a frame) if it contains mutually exclusive and exhaustive possible answers to a question. It is usually denoted as Θ. It is required that one and only one element in the set is true at any time.

For instance, if we assume that Emma lives in one of the cities, $city_1, city_2, \ldots, city_6$, then, $\Theta = \{city_1, city_2, city_3, city_4, city_5, city_6\}$ is a frame of discernment for the question 'In which city does Emma live?'. Thus, for Example 1, $\Theta_{Ex.1} = \{A, \overline{A}\}$. However, the frame of discernment for Example 2 is $\Theta_{Ex.2} = \{W, G, B\}$, where W, G, B represents "white," "gray," "black," respectively.

Definition 2 (*Mass Function*). A function m: $2^{\Theta} \to [0,1]$ is called a mass function on frame Θ if it satisfies the following two conditions:

a. $m(\emptyset) = 0$, and
b. $\Sigma_A m(A) = 1$,

where $\emptyset$ is an empty set and A is a subset of Θ.

A mass function is also called *a basic probability assignment*, denoted as *bpa*. For instance, if we know that Emma lives in the area covering the six cities, but we have no knowledge about in which city she lives, then we can only give a mass function $m(\Theta) = 1$. Alternatively, if we know that Emma lived in $city_3$ two years ago and she intended to move to other cities and tried to find a job somewhere within these six cities, but we have no definite information about where she lives now, then a mass function could be defined as $m(\{city_3\}) = p, m(\Theta) = 1 - p$, where p stands for the degree of our belief that she still lives in $city_3$.

In Example 1, the event space is binary – either the suspect is in space A or not, $\overline{A}$. From the detective's assessment, $m(\emptyset) \equiv 0$, $m(\overline{A}) = 0.2$, $m(A) = 0.4$, and $m(A \cup \overline{A}) = 0.4$. Note that $m(A) + m(\overline{A}) + m(A \cup \overline{A}) = 1$.

In Example 2, the event space has the three singletons: W, G, and B. Suppose that the person reporting the results of the draws says "white" 5% of the time, "gray" never, "black" 5% of the time, "not black" 15% of the time (note that "not black" = "white or gray"), "not gray" 10% of the time, "not white" 5% of the time, and "I drew a ball" the remaining 60% of the time. Thus, $m(\emptyset) \equiv 0$, $m(W) = 0.05$, $m(G) = 0.0$, $m(B) = 0.05$, $m(W \cup G) = 0.15$, $m(W \cup B) = 0.10$, $m(G \cup B) = 0.05$, and $m(W \cup G \cup B) = 0.60$.

Definition 3 (*Belief Function*). A function: $bel : 2^{\Theta} \to [0, 1]$ is called a belief function if bel satisfies:

a. $bel(\Theta) = 1$;
b. $bel(\cup_1^n A_i) \geqslant \sum_i bel(A_i) - \sum_{i>j} bel(A_i \cap A_j) + \cdots + (-1)^{-n} bel(\cap_i A_i)$.

It is easy to see that $bel(\emptyset) = 0$ for any belief function. A belief function is also called *a support function*. The difference between $m(A)$ and $bel(A)$ is that $m(A)$ is our belief committed to the subset A excluding any of its subsets while $bel(A)$ is our degree of belief in A as well as all of its subsets.

In general, if m is a mass function on frame Θ then bel defined in (1) is a belief function on Θ:

$$bel(B) = \Sigma_{A \subseteq B} m(A) \tag{1}$$

Referring to our running examples, the power set in Example 1 is $2^{\Theta_{Ex.1}} = \{\emptyset, A, \bar{A}, (A \cup \bar{A})\}$. The mass function is $m_{Ex.1}(x) : 2^{\Theta_{Ex.1}} = \{0, 0.4, 0.2, 0.4\}$. The belief function is $bel_{Ex.1}(x) = \sum_{x \subseteq A} m(x) = \{0, 0.4, 0.2, 1\}$. In Example 2, the power set is $2^{\Theta_{Ex.2}} = \{\emptyset, W, G, B, (W \cup G), (W \cup B), (G \cup B), (W \cup G \cup B)\}$. The mass function is $m_{Ex.2}(x) = \{0, 0.05, 0, 0.05, 0.15, 0.10, 0.05, 0.60\}$. The belief function is $bel_{Ex.2}(x) = \{0.00, 0.05, 0.00, 0.05, 0.20, 0.20, 0.10, 1.00\}$.

Recovering a mass function from a belief function is as follows [35]:

$$m(A) = \Sigma_{B \subseteq A} (-1)^{|B|} bel(B)$$

For any finite frame, it is always possible to get the corresponding mass function from a belief function and the mass function is unique.

A subset A with $m(A) > 0$ is called a *focal element of this belief function*. If all focal elements of a belief function are the singletons of Θ then the corresponding mass function is exactly a probability distribution on Θ. So mass functions are generalized probability distributions in this sense. In Example 2, the focal elements are all members of $2^{\Theta_{Ex.2}}$ with the exception of $\emptyset$ and G as the mass of both are zero.

If there is only one focal element for a belief function and the focal element is the whole frame Θ, this belief function is called a *vacuous belief function*. It represents total ignorance (because of lack of knowledge). To illustrate this concept, let us revisit Example 1. If the detective has no idea about the presence of the suspect in area A, then $m(x) : 2^{\Theta_{Ex.1}} = \{0, 0, 0, 1\}$. Here, we have a vacuous belief function as the only non-zero mass is $m(A \cup \bar{A}) = 1$ so that $bel(x) = \{0, 0, 0, 1\}$.

Definition 4 (*Plausibility Function*). A function pls defined below is called a plausibility function $pls(A) = 1 - bel(\bar{A})$.

where $pls(A)$ represents the degree to which the evidence fails to refute A. From a mass function, we can get its plausibility function as [35]:

$$pls(B) = \Sigma_{A \cap B6 = \emptyset} m(A) \tag{2}$$

For our running examples, the plausibility for Example 1 is $pls_{Ex.1}(x) = \{0, 0.8, 0.6, 1.0\}$. In Example 2, $pls_{Ex.2}(x) = \{0, 0.90, 0.85, 0.95, 0.75, 0.95, 1.00\}$.

2.1.1.1. Bayesian belief as a special case of the D–S belief structure. Note that the singleton event in the frame of discernment is contained in the power set, that is $\Theta \subset 2^{\Theta}$. D–S belief reduces to Bayesian belief for the special case where the masses of all singletons add to one – all tuples have zero mass. For example, if in Example 2, the results were 40%, 20%, and 40% for the singleton events of white, gray and black, respectively, all masses for the tuples, such as $m(W \cup G)$, are zero. In this case, the mass function becomes $m_{Ex.2_{Bayesian}}(x) : 2^{\Theta_{Ex.2}} = \{0, 0.4, 0.2, 0.4, 0, 0, 0, 0\}$. The belief and plausibility functions become equal such that $bel_{Ex.2_{Bayesian}}(x) = pls_{Ex.2_{Bayesian}}(x) = \{0, 0.4, 0.2, 0.4, 0.6, 0.8, 0.6, 1\}$ because the singletons add to one for the Bayesian case.

Formally, singleton masses are *normal* for the Bayesian case and *sub-normal* in general for the D–S case. Furthermore, D–S structures have "super-additive" belief, and "sub-additive" plausibility. In Example 2 for the D–S case, $bel(W \cup G) = 0.15 > bel(W) + bel(G) = 0.05$ and $pls(W \cup G) = 0.95 < pls(W) + pls(G) = 1.7$ All three properties reduce to "additive" in the special Bayesian case.

2.1.1.2. Multiple frames of discernment. When more than one mass function is given on the same frame of discernment, the combined impact of these pieces of evidence is obtained using a mathematical formula called *Dempster's combination rule*.

Definition 5. Let m_1 and m_2 be two bbas, and let $m_1 \oplus m_2$ be the combined bba.

$$m_1 \oplus m_2(C) = \frac{\Sigma_{A \cap B = C}(m_1(A) \times m_2(B))}{1 - \Sigma_{A \cap B = \emptyset}(m_1(A) \times m_2(B))}, \quad \text{for } C \neq \emptyset$$

When $m_1 \oplus m_2(\emptyset) = \Sigma_{A \cap B = \emptyset}(m_1(A) \times m_2(B)) = 1$, the two pieces of evidence totally contradict with each other and cannot be combined with the rule. The condition of using the rule is stated as "two or more pieces of evidence are based on distinct bodies of evidence" [35].

Definition 6 [37]. Let m be a bba on Ω. Its associated pignistic probability function $BetP_m : \Omega \to [0, 1]$ is defined as:

$$BetP_m(\omega) = \sum_{A \subseteq \Omega, \omega \in A} \frac{1}{|A|} \frac{m(A)}{1 - m(\emptyset)}, \quad m(\emptyset) \neq 1 \tag{3}$$

where $|A|$ is the cardinality of subset A.

The transformation from m to $BetP_m$ is called the *pignistic transformation*. When an initial *bba* gives $m(\emptyset) = 0, \frac{m(A)}{1 - m(\emptyset)}$ is reduced to $m(A)$. Value $BetP_m(A)$ is referred to as the *betting commitment to A*.

The main purpose of inducing a probability distribution is for decision making such as computing expected utilities in the decision theory. That is, evidence is assumed to be modeled at the *credal level* while decisions are at the pignistic level.

On the other hand, evidence may not always be gathered over the frame (or problem space) on which a decision will be made. In many cases, decisions are made over a space that evidence will not be directly observed (whether we shall take an umbrella) but evidence can be mapped to decision choices (if it rains, then take an umbrella, otherwise, not, and whether it rains or not is observable). When this is the case, a multivalued mapping function will be required, which in fact was the original idea of Dempster's for generating a mass function.

Definition 7. Given two distinct frames Ω and Θ, function $\Gamma : \Omega \to 2^{\Theta}$ defines a multivalued mapping as:

$$\Gamma(\omega) = X, \quad \forall \omega \in \Omega, \exists X \subseteq \Theta \tag{4}$$

From this multivalued mapping, any probability distribution observed over one frame can be propagated to another to induce a mass function. Uncertain mappings as well as evidence modeled as a mass function on the first frame (Ω) can also be propagated to the second frame using approaches proposed in [22].

2.1.1.3. When do we use Bayesian over D–S beliefs?. The downside to using D–S theory is the computational expense since the belief structure is based upon the power set. The BPAs scale exponentially as $2^{|\Theta|}$. Hence, the practitioner should use Bayesian beliefs when the there is enough knowledge to model the uncertainty adequately by singleton masses alone. Indeed, one could still use D–S theory, since it is a generalization of probability theory. Such a task; however, is akin to using Einstein's general relativity instead of Newtonian mechanics to calculate the path of ball that we toss across a room. It just would not be done!

On the other hand, we may need D–S beliefs when: (1) incomplete information is a significant component of the uncertainty; and (2) use of maximum entropy as done in Bayesian beliefs is inappropriate. This latter point represents a fundamental difference for the representation of ignorance between the two approaches. For example if in Example 1, all five experts said "I don't know" as to whether or not the suspect is in A, the D–S belief structure would be $m(A) = 0$, $m(\overline{A}) = 0$, Z and $m(A \cup \overline{A}) = 1$. For the Bayesian belief structure, $m(A) = m(\overline{A}) = 1/2$. This latter structure says implies that the suspect is in the area 50% of the time, when in reality, we have no knowledge for this assessment.

Practitioners that need to use D–S based models should look for sparsity or approximate sparseness in the belief-structure in order to reduce the computational expense should it become impractical.

$$\Pi(A) = \max(\{\pi(\omega) | \omega \in A\}) \quad \text{and} \quad N(A) = 1 - \Pi(A^{-}) \tag{5}$$

$$\Pi(2^{\Omega}) = 1 \quad \text{and} \quad \Pi(\varnothing) = 0 \tag{6}$$

$$\Pi(A \cup B) = \max(\Pi(A), \Pi(B)) \quad \text{and}$$
$$N(A \cap B) = \min(N(A), N(B)) \tag{7}$$

π is said to be normal if there exists $\omega_0 \in \Omega$ such that $\pi(\omega_0) = 1$. It is not always possible to obtain a possibility distribution from a piece of evidence. Most of the time, uncertain information is expressed as a set of weighted subsets (or a set of weighted formulas in possibilistic logic). A weighted subset (A, α) is interpreted as that the necessity degree of A is at least to α, that is, $N(A) \geqslant \alpha$.

Let $\Omega = \{\omega_1, \ldots, \omega_n\}$, and a subset of Ω is denoted as $A_i = \{\omega_{i1}, \ldots, \omega_{ix}\}$ to make the subsequent description simpler. In this way, a set of weighted subsets constructed from a piece of uncertain information is defined as $\{(A_i, \alpha_i), i = 1, \ldots, p\}$, where α_i is the lower bound on the degree of necessity $N(A_i)$. In the following, a set of weighted subsets is called a *possibilistic information base (PIB for short)* and denote such a base as K.

There is normally a family of possibility distributions associated with a given K, with each of the distributions π satisfying the condition:

$$1 - \max\{\pi(\omega) | \omega \in \overline{A}_i^{-}\} \geqslant \alpha_i$$

which guarantees that $N(A_i) \geqslant \alpha_i$. Let $\{\pi_j, j = 1, \ldots, m\}$ be all the possibility distributions that are compatible with $K = \{(A_i, \alpha_i), i = 1, \ldots, p\}$. A possibility distribution $\pi_l \in \{\pi_j, j = 1, \ldots, m\}$ is said to be the least specific possibility distribution among $\{\pi_j, j = 1, \ldots, m\}$ if $\nexists \pi_t \in \{\pi_j, j = 1, \ldots, m\}, \pi_t 6 \neq \pi_l$ such that $\forall \omega, \pi_t(\omega) \geqslant \pi_l(\omega)$.

A common method to select one of the compatible possibility distributions is to use the *minimum specificity principle* which allocates the greatest possibility degrees in agreement with the constraints $N(A_i) \geqslant \alpha_i$. This possibility distribution always exists and is defined as follows:

$$\forall \omega \in \Omega, \pi(\omega) = \begin{cases} \min\{1 - \alpha_i | \omega \notin A_i\} = 1 - \max\{\alpha_i | \omega \notin A_i\} & \text{when } \exists A_i \text{ s.t. } \omega \notin A_i \\ 1 & \text{otherwise} \end{cases} \tag{8}$$

2.1.2. Relationship with possibility theory

Possibility theory is another popular choice for representing uncertain information. A basic function in possibility theory is a *possibility distribution* denoted as π which assigns each possible world in the frame of discernment Ω a value in $[0, 1]$.

From a possibility distribution, two measures are derived, a possibility measure (denoted as Π) and a necessity measure (denoted as N). The former estimates to what extent the true event is believed to be in the subset and the latter evaluates the degree of necessity that the subset is true. The relationships between π, Π and N are as follows:

A possibility distribution is not normal if $\forall \omega, \pi(\omega) < 1$. The value $1 - \max_{\omega \in \Omega} \pi(\omega)$ is called *the degree of inconsistency* of K and is denoted as $Inc(K)$.

The two basic combination modes in possibility theory are the *conjunctive* and the *disjunctive* modes for merging possibility distributions [5] when n possibility distributions are given on the same frame of discernment. For example, if we choose min and max as the conjunctive and disjunctive operators respectively, then:

$$\forall \omega \in \Omega, \pi_{cm}(\omega) = \min_{i=1}^{n}(\pi_i(\omega)), \forall \omega \in \Omega, \pi_{dm}(\omega)$$
$$= \max_{i=1}^{n}(\pi_i(\omega)) \tag{9}$$

When all the sources are believed reliable and these sources agree with each other, a conjunction operator is used. On the other hand, a disjunctive operator is applied when it is believed that some sources are reliable but it is not known which of these sources are. A conjunction operator can lead to a new possibility distribution that is not normal when some sources are not in agreement, even though all the original possibility distributions are normal. When this happens, the merged possibility distribution expresses an inconsistency among the sources.

A belief function is said to be *consonant* if its focal elements are nested [35]. That is, if $S_1, S_2, \ldots, S_n$ are the focal elements of a mass function, then it is possible to re-arrange these focal elements in such an ascending order that for any pair of neighboring subsets, the latter is a superset of the former, e.g., $S_1 \subset S_2 \subset \cdots \subset S_n$ after re-subscript indexing.

Let *Bel* be a consonant function, and *Pl* be its corresponding plausibility function, *Bel* and *Pl* have the following properties:

$$Bel(A \cap B) = \min(Bel(A), Bel(B)) \quad \text{for all } A, B \subseteq 2^{\Omega}$$
$$Pl(A \cup B) = \max(Pl(A), Pl(B)) \quad \text{for all } A, B \subseteq 2^{\Omega}$$

These two properties correspond to exactly the requirements of necessity and possibility measures in possibility theory. Necessity and possibility measures are special cases of belief and plausibility functions.

Furthermore, a *contour function* $f :\rightarrow [0, 1]$, for a consonant function is defined using equation $f(\omega) = Pl(\{\omega\})$.

For a subset $A \subseteq \Omega$,

$$Pl(A) = \max_{\omega \in A} f(\omega) \tag{10}$$

Eq. (10) matches the definition of possibility measure from a possibility distribution, so a contour function is a possibility distribution.

Let π be a possibility distribution on frame of discernment Ω and is normal. Let $B_1, B_2, \ldots, B_p$ and B_{p+1} be disjoint subsets of Ω such that:

(1) $\pi(\omega_1) = \pi(\omega_2)$ when $\omega_1, \omega_2 \in B_i$;
(2) $\pi(\omega_1) > \pi(\omega_2)$ if $\omega_i \in B_i$ and $\omega_j \in B_{i+1}$;
(3) $\pi(\omega_i) = 0$ if $\omega_i \in B_{p+1}$.

Let $m(A_i) = \pi(\omega_i) - \pi(\omega_j)$ where $\omega_i \in B_i$ and $\omega_j \in B_{i+1}$ for $i = 1, \ldots, p$, then m is a mass function on focal elements A_i.

Example 3:

Let π be a possibility distribution on $\Omega = \{\omega_1, \ldots, \omega_4\}$ where $\pi(\omega_1) = 0.7$, $\pi(\omega_2) = 1.0$, $\pi(\omega_3) = 0.8$, and $\pi(\omega_4) = 0.7$. The disjoint subsets for π are as follows: $B_1 = \{\omega_2\}$, $B_2 = \{\omega_3\}$, $B_3 = \{\omega_1, \omega_4\}$; and the corresponding focal elements as well as *bba* m are as follows: $A1 = B1$, $A2 = B1 \cup B2$, $A3 = B1 \cup B2 \cup B3$, $m(A_1) = 0.2$, $m(A_2) = 0.1$, and $m(A_3) = 0.7$.

2.1.3. Information fusion with D–S theory

Information fusion can be viewed as an aggregation process which aims to extract truthful knowledge from information coming from various sources. Information fusion is particularly related to the issue of uncertainty modeling and reliability measures, through identifying conflict, resolving conflict and discounting unreliable sources when producing a final result. There are many approaches and theories for modeling information, and the information fusion problem has been discussed in each of these settings almost independently. Most of the time, specialized principles or properties have been proposed in order to characterize the specific features of the fusion process in the language of each particular formal setting. We look at some of the most general properties that a fusion rule (e.g., Dempster's rule) shall comply, and use these set of rules to check some of the best known combinations rules in D–S theory as discussed in [15].

Property 1 (*Unanimity*). When all sources agree on some results, then the latter should be preserved.

Property 2 (*Informational Monotony*). If a set of agents provides less information than another set of *non-disagreeing* agents, then fusing the former inputs should not produce a more informative result than fusing the latter.

Property 3 (*Consistency Enforcement*). This property requires that fusing individually consistent inputs should give a consistent result.

Property 4 (*Optimism*). In the absence of specific information about source reliability, one should assume as many sources as possible are reliable, in agreement with their observed mutual consistency.

Property 5 (*Fairness*). The fusion result should treat all sources on a par. Hence, the result of the fusion process should keep something from each input.

Property 6 (*Insensitivity to Vacuous Information*). Sources that provide vacuous information should not affect the fusion result.

Property 7 (*Commutativity*). Inputs from multiple sources are treated on a par, and the combination should be symmetric (up to their relative reliability).

The four famous rules, Dempster's combination rule, Dubois/Prade rule [14], Yager's rule [45], and Smets' rule [36] satisfy most of these properties in different ways. Readers interested in details of these examinations can find full discussions presented by Dubois et al. [15].

2.2. Non-statistical approaches

Here we consider how both fuzzy set and rough set theory have been used to represent geospatial data with uncertainty.

2.2.1. Fuzzy set/possibility theory

The utilization of fuzzy set approaches for modeling uncertainty in spatial data has been considered frequently after the introduction of fuzzy sets by Zadeh [49]. For example, the use of fuzzy set approaches in geographical research involves areas such as geographical decision-making and behavioral geography [17,18]. However, the most consistent early approach using fuzzy set theory in applications to GIS was developed initially by Robinson and Frank [31] where they considered several models appropriate to this situation including fuzzy database representations using simple membership values in relations, and a similarity-based approach for geospatial features. An application for which both the data as well as spatial relationships are imprecise, was modeled using imprecision intrinsic to natural language which is possibilistic [48] in nature.

A number of subsequent models using fuzzy set approaches for applications involving spatial uncertainty have been developed. These included among others: querying spatial information [42], representing spatial relationships [9], and object-oriented modeling [12,11]. Models have been proposed as well that allow for enhancing the representation in databases for the management of uncertain geospatial data [27].

2.2.1.1. Fuzzy set theory background. Extensions to ordinary set theory, known as fuzzy set theory, provide widely recognized representations of imprecision and vagueness [49]. This section overviews some basic concepts of fuzzy sets and a more complete introduction can be found in several comprehensive sources [29,47].

Ordinarily a set S is specified by its characteristic function $C : S \to \{0, 1\}$ If U is the universal set from which values of S are taken, then, we can represent S as:

$$S = \{x | x \in U \wedge C(x) = 1\} \tag{11}$$

This is the representation for a crisp or non-fuzzy set. However, for a fuzzy set A, we have a membership function; $\mu_A : A \to [0, 1]$.

$$A = \{x | x \in U \wedge \mu_A > 0\} \tag{12}$$

That is, for a fuzzy set, the characteristic function takes on all values between 0 and 1 and not just the discrete values of 0 or 1 representing the binary choice for membership in a conventional crisp set such as S. For a fuzzy set, the characteristic function is often called the membership function. As an example of a fuzzy set, consider a description of mountainous terrain. We want to use a linguistic terminology to represent whether an estimate of elevation is viewed as low, medium, or high. If we assume we have obtained opinions of experts knowledgeable about such terrain, we can define fuzzy sets for these terms. Clearly, it is reasonable to represent these as fuzzy sets as they represent judgmental opinions and cannot validly be given precise specification. Here we will provide a typical representation of a fuzzy set A for "*HIGH*" in terms of the height in kilometers (K):

$$A_{HIGH} = \{0.0/0.1K, 0.125/0.5K, 0.5/1K, 0.8/2K, 0.9/3K, 1.0/4K\}$$

This typical representation enumerates selected elements and their respective membership values as $\mu_A(x)/x$. It is also common to more fully specify the membership function $\mu_A(x)$ in an analytic form or as a graphical depiction. The membership function for the representation shown as in A_{HIGH} could be fully specified by interpolation between the consecutive elements. Also, extrapolation past the first and last elements completes the specification, i.e., $\mu_A(x) = 0.0x \leqslant 0.1K$ and $\mu_A(x) = 1.0x \geqslant 4K$.

2.2.1.2. Fuzzy set operations. All of the basic set operations must have equivalent ones in fuzzy sets, but there are additional operations based on membership values of a fuzzy set that have no correspondence in crisp sets. We will use the membership functions μ_A and μ_B to represent the fuzzy sets A and B involved in the operations to be illustrated.

Set equality:	$A = B : \mu_A(x) = \mu_B(x)$
Set containment:	$A \subseteq B : \mu_A(x) \leqslant \mu_B(x)$
Set complement:	$\overline{A} = \{[1 - \mu_A(x)]/x\}$

For ordinary crisp sets $A \cap \overline{A} = \varnothing$; however, this is not generally true for a fuzzy set and its complement. This may seem to violate the law of the excluded middle, but this is just the essential nature of fuzzy sets. Since fuzzy sets have imprecise boundaries, we cannot place an element exclusively in a set or its complement.

Set union:	$A \cup B : \mu_{A\cup B}(x) = \mathrm{Max}(\mu_A(x), \mu_B(x))$
Set intersection:	$A \cap B : \mu_{A\cap B}(x) = \mathrm{Min}(\mu_A(x), \mu_B(x))$

With these definitions, the standard properties for crisp sets of commutativity, associativity, and so forth, hold as well for fuzzy sets.

Another interpretation of membership functions of fuzzy sets as possibility distributions provides the encoding for flexible constraints induced by natural language statements [48]. Π is a possibility distribution: $\Pi : X \to [0, 1]$ where $\pi(x_i)$ gives the possibility that x_i is the value of a variable V, $i = 1, \ldots, n$. Note that when we associate a fuzzy set A with the variable V, this will specify a possibility distribution of V in terms of the membership function of A: $\Pi_V(x) = \mu_A(x)$.

A usual requirement for a possibility distribution is the normality condition, $\mathrm{Max}_x\ [\pi(x_i)] = 1,\ i = 1, \ldots, n$. This means that at least one element in X must be fully possible.

2.2.2. Rough set theory

Another approach for uncertainty representation uses the rough set theory [28] concept of indiscernibility of values. The indiscernibility relation is used to partition domains into equivalence classes, and lower- and upper-approximation regions for distinguishing between certain and possible (or partial) inclusion in a rough set. The indiscernibility relation permits grouping of items based on some definition of 'equivalence,' which basically depends on the application domain. This partitioning can be used

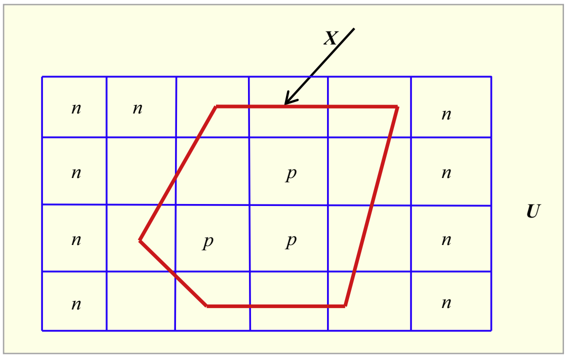

Fig. 3. Illustration of the concept of a rough set *X*.

to increase or decrease the granularity of a domain, to group items together that are considered indiscernible for a given application, or to "bin" ordered domains into range groups.

Many researchers have considered rough set approaches to modeling geospatial uncertainty. A description of spatial data using rough sets, focusing on a formal modeling framework for realm-based spatial data types can be found in [34]. Worboys [44] developed a model for imprecision based on the resolution of spatial data and applied it to the integration of such data. This approach relies on the use of indiscernibility – a central concept in rough sets. Ahlqvist et al. [1] introduced an approach for rough classification of spatial data and representation of inexact spatial locations using rough sets. Wang et al. [43] established an approach for the field representation of a spatial entity using a rough raster space which was evaluated for remote sensing images in a classification case study. Bittner and Stell [7] proposed the partitions' relationship to rough sets and approximated map objects with vague boundaries using *K*-labeled partitions, which can represent maps. More refined levels of details or granularity can be obtained by using stratified rough partitions for map scale transformations.

2.2.2.1. Rough set theory background. Here we provide an overview of the basics of rough set theory. The following is a set of common terminology and notation for rough sets

U	is the universe, which cannot be empty,
R	indiscernibility relation, or equivalence relation,
$A = (U,R)$	is an ordered pair, called an approximation space,
$[x]R$	denotes the equivalence class of R containing x, for any element x of U, elementary sets in A – the equivalence classes of R.

Any finite union of these elementary sets in A is called a definable set. A particular rough set $X \subseteq U$, however, is defined in terms of the definable sets by specifying its lower $\underline{R}(X)$ and upper $(\overline{R}X)$ approximation regions:

$$\underline{R}X = \{x \in U | [x]R \subseteq X\}$$

and

$$\overline{R}X = \{x \in U | [x]R \cap X \neq \varnothing\}.$$

where $\underline{R}X$ is the R-positive region, $U - \overline{R}X$ is the R-negative region, and $\overline{R}X - \underline{R}X$ is the R-boundary or R-borderline region of the rough set X.

This allows for the distinction between certain and possible inclusion in a rough set. The set approximation regions provide a mechanism for determining whether something certainly belongs to the rough set, may belong to the rough set, or certainly does not belong to the rough set. X is called R-definable if and only if $\underline{R}X = \overline{R}X$. Otherwise, $\underline{R}X \neq \overline{R}X$ and X is rough with respect to R. In Fig. 3,

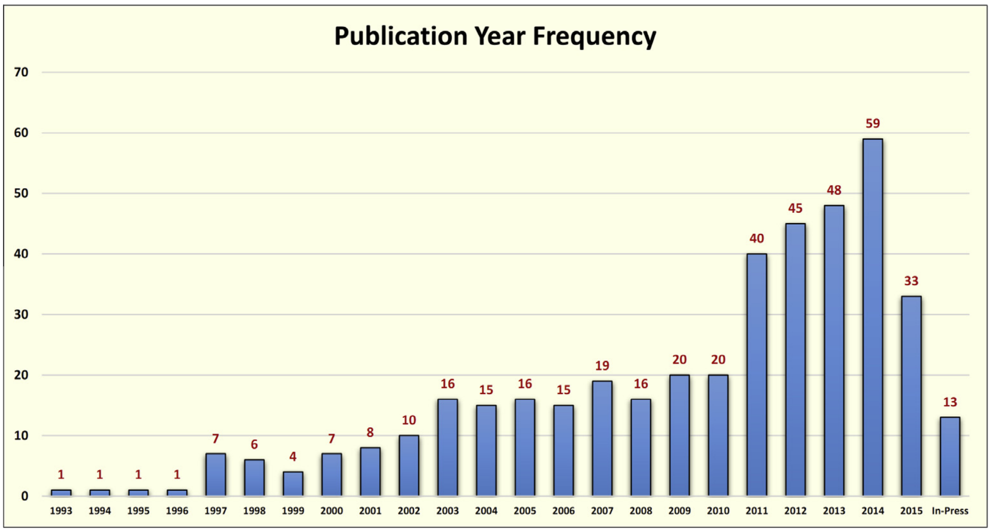

Fig. 4. Frequency of the publication year.

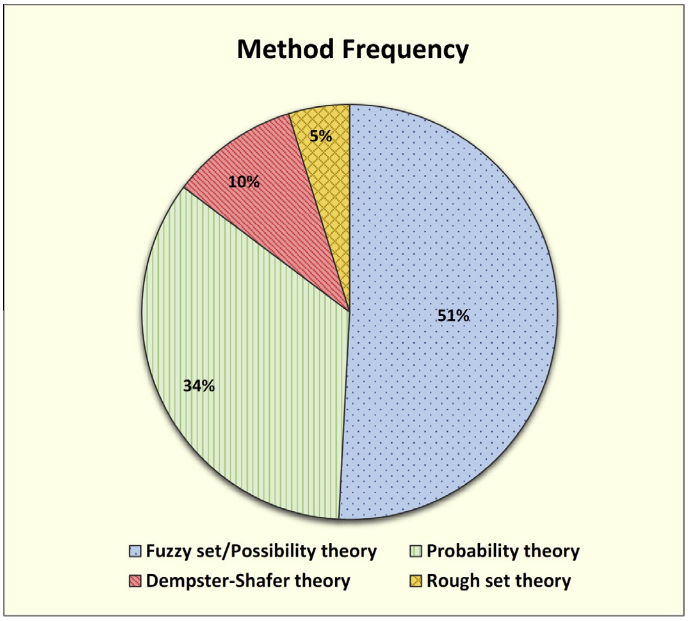

Fig. 5. Frequency of the uncertain spatial data modeling method used in GIS.

Table 1
Frequency of fuzzy set/possibility theory methods.

Fuzzy set/possibility theory method	Frequency
Fuzzy membership	111
Fuzzy AHP	35
Fuzzy multi-criteria analysis	18
Fuzzy rules	10
Neuro fuzzy	9
Fuzzy classification	7
Adaptive neuro-fuzzy inference system (ANFIS)	5
Possibility theory	4
Fuzzy C-means	3
Mamdani's fuzzy inference modeling	3
Fuzzy cellular automata	1
Fuzzy cognitive modeling	1
Fuzzy constrained method	1
Fuzzy *k*-means	1
Fuzzy majority procedure	1
FUZZY ordered weighted average	1
Fuzzy pattern recognition	1
Fuzzy risk modeling	1
Gray relational analysis	1
Total	214

the universe U is partitioned into equivalence classes denoted by the rectangles. Those elements in the lower approximation of X, $\underline{R}X$, are denoted by the letter "p" and elements in the R-negative region by the letter "n". All other classes belong to the boundary region of the upper approximation.

To obtain possible results, in addition to the obvious, when querying an ordinary spatial information system, we may employ the use of the boundary region information in addition to that of the lower approximation region. The results in the lower-approximation region are certain, corresponding to exact matches. The boundary region of the upper-approximation contains those results that are possible, but not certain.

The approximation regions of rough sets are useful when information related to spatial data regions is queried [3]. Consider a region such as a woodland. One can reasonably conclude that any grid point labeled as "woods" which on all sides is surrounded by grid points also classified as "woods" is, indeed a point characterized by the feature "woods." But we may also be interested in grid points labeled as "woods" that adjoin points identified as "field." It is possible that such points represent field areas as well as forest areas but were identified as "woods" during the classification. Likewise, points identified as "field" but adjacent to "woods" points may represent areas that contain part of the forest.

If we force a finer granulation of the partitioning, a smaller boundary region results. This occurs when the resolution is increased. As the partitioning becomes finer and finer, a point is finally reached where the boundary region is non-existent. The upper- and lower-approximation regions are then the same and there is no uncertainty in the spatial data as can be determined by the representation of the model.

3. Literature review of GIS applications

In this study, we conducted a comprehensive and methodic survey of papers where probability theory, D–S theory, fuzzy/set/possibility theory, and rough set theory were used in GIS applications to model uncertain spatial data. We found 421 relevant papers listed in our bibliographical list of GIS papers with uncertain spatial data (Appendix A). Appendix B provides a complete listing of the methods, applications, and locations for the papers reviewed in this study. Looking at the year of the publications in Fig. 4, the majority of the papers are published

Table 2
Frequency of probability theory methods.

Probability theory method	Frequency
General probability theory	92
Bayesian probability	21
Probability map	21
Transition probability	6
Frequency ratio	5
Total	145

during the past five years where the average number of such papers has doubled in those years.

We then considered the methods used in these papers to model uncertain spatial data in GIS applications. As shown in Fig. 5, 214 (51%) papers used fuzzy set/possibility theory, 145 (34%) papers used probability theory, 42 (10%) papers used D–S theory, and 20 (5%) papers used rough set theory. In general, statistical methods are the preferred methods for handling uncertain spatial data in GIS when prior knowledge is available and non-statistical methods are used when vagueness and ambiguities result from the imprecision of the meaning of a concept in geospatial data.

We then further studied different methods used in the 214 fuzzy set/possibility theory and probability theory papers. As shown in Table 1, fuzzy membership, fuzzy Analytic Hierarchy Process (AHP), fuzzy multi-criteria analysis, fuzzy rules, and neuro fuzzy methods are the most commonly used techniques in GIS. The analysis shows that the pervasive use of fuzzy membership indicates the power of this concept and the fact that it is extremely useful in capturing the vagueness and ambiguity associated with the natural environment. Multi-criteria decision making refers to a general collection of methods widely used for making decision in the presence of multiple and often conflicting criteria. The AHP is a multi-criteria decision making approach and was introduced by Saaty [32,33]. Spatial decision problems typically involve a large set of feasible alternatives and multiple and often conflicting evaluation criteria. The combination of multi-criteria decision making and GIS benefit from the rich collection of the multi-criteria tools and procedures for structuring decision problems and evaluating decision alternatives and the capabilities of GIS as a problem solving tool for spatially referenced data. Malczewski [24] presents a comprehensive a survey of the GIS-based multi-criteria decision analysis literature.

Next, we analyzed different methods used in the 145 application using probability theory. As shown in Table 2, general probability theory, Bayesian probability, and probability map are most commonly used in GIS. Our review showed that while general probability theory and frequency distribution is naturally the most widely used statistical method, Bayesian probabilities are also very popular among the GIS researchers. Bayesian probabilities are used not only to proceed from causes to consequences, but also to deduce the probabilities of different causes given the consequences. Uusitalo [39] presents advantages and challenges of Bayesian probabilities in environmental modeling and Ellison [16] provides a comprehensive review of the differences of Bayesian and frequentist probabilities.

Next, we studied different applications where one of the statistical and non-statistical methods is used in GIS. As shown in Table 3, landslide susceptibility modeling, land suitability modeling, natural hazard modeling, groundwater resource modeling, land use modeling, soil suitability modeling, urban planning and modeling, mineral potential modeling, and marine environmental modeling were among the most common uncertain spatial data applications in GIS. As broad characterization we see that hazard/disaster prediction and general planning encompass the majority of these applications. It is not surprising to see landslide susceptibility modeling as one of the most widely used application of GIS since over the last two decades a wider range of methods have been proposed to improve the prediction and mapping of landslide susceptibility. Binaghi et al. [6] discussed the limitations of GIS in addressing different layers of data for landslide modeling and recommended using soft computing approaches (such as fuzzy set theory, neural networks, probabilistic, and evidential approaches) for handling uncertain spatial data in landslide research. Chacón et al. [8] provide an excellent review of the landslide susceptibility research and Malczewski [24] presents a critical overview of the GIS-based land-use suitability analysis.

We then examined the locations (country/region) where the 421 studies were conducted. As shown in Table 4, most studies are conducted in China, Iran, United States, India, Korea, Australia, Turkey, Canada, Greece, Spain, Malaysia, Italy, Taiwan, and Germany. It is understandable that China has the most of such publications

Table 3
Frequency of applications.

Application	Frequency
Landslide susceptibility modeling	98
Land suitability modeling	51
Natural hazard modeling	38
Groundwater resource modeling	27
Land use modeling	23
Soil suitability modeling	22
Urban planning and modeling	22
Mineral potential modeling	18
Marine environmental modeling	15
Health risk modeling	8
Environmental modeling	7
Geo-historical modeling	7
Soil salinization modeling	6
Ground subsidence modeling	5
Wilderness land modeling	5
Habitat suitability modeling	4
Coastal modeling	3
Mineral resources modeling	3
Rock-fall susceptibility modeling	3
Water quality modeling	3
Air pollution modeling	2
Forest management modeling	2
Geothermal modeling	2
Land degradation modeling	2
Site suitability modeling	2
Underground vulnerability modeling	2
Others	41
Total	421

Table 4
Country data.

Country/region	Frequency
China	62
Iran	49
USA	30
India	29
Korea	20
Australia	18
Turkey	14
Canada	13
Greece	11
Spain	11
Malaysia	10
Italy	9
Taiwan	9
Germany	8
France	5
Japan	5
Vietnam	5
Ecuador	4
Nepal	4
Saudi Arabia	4
Brazil	3
Ireland	3
Israel	3
Malaysia	3
Mexico	3
New Zealand	3
Thailand	3
Others	72
Not available	8
Total	421

Table 5
Journal data.

Journal	Frequency
Natural Hazards	29
Environmental Earth Sciences	22
Computers and Geosciences	17
Arabian Journal of Geosciences	10
Environmental Geology	10
International Journal of Geographical Information Science	10
Ecological Modelling	8
Geoderma	8
Environmental Management	7
Journal of Environmental Management	7
Natural Resources Research	7
CATENA	6
Computers, Environment and Urban Systems	6
Engineering Geology	6
Environmental Modelling and Software	6
Applied Geography	5
Environmental Monitoring and Assessment	5
Geomorphology	5
Hydrogeology Journal	5
Journal of the Indian Society of Remote Sensing	5
Landscape and Urban Planning	5
Agricultural Systems	4
Agriculture, Ecosystems and Environment	4
Computers and Electronics in Agriculture	4
Environmental Modeling and Assessment	4
International Journal of Applied Earth Observation and Geoinformation	4
Journal of Earth System Science	4
Journal of Geographical Systems	4
Journal of Mountain Science	4
Landslides	4
Applied Geomatics	3
Applied Mechanics and Materials	3
Bulletin of Engineering Geology and the Environment	3
Ecological Informatics	3
GeoJournal	3
Journal for Nature Conservation	3
Journal of Asian Earth Sciences	3
Journal of Geographical Sciences	3
Journal of Hydrology	3
Landscape Ecology	3
Stochastic Environmental Research and Risk Assessment	3
Transactions in GIS	3
Others	160
Total	421

based on its rapid growth and development in last decade. For Iran, it is possible that the common occurrences of earthquakes and such natural disasters have influenced such publications. Overall, the data shows that the applications of uncertain spatial data in GIS is more common in countries with very diverse geophysical landscape and climatic conditions.

Finally, we considered the journals where these 421 papers appeared. As shown in Table 5, Natural Hazards, Environmental Earth Sciences, Computers and Geosciences, Arabian Journal of Geosciences, Environmental Geology, and International Journal of Geographical Information Science were the journals that had the most published papers on managing uncertain spatial data in GIS.

4. Conclusion and future research directions

GIS have become critical components of the global cyberinfrastructure and converging technological trends such as global positioning tools and geo-enabled devices have provided many opportunities for GIS applications. Our literature survey highlights the importance of representing and managing uncertainty in GIS applications. We note that in recent years, an increasing number of publications have used both statistical and non-statistical methods to solve such problems. Statistical methods are better suited for handling uncertain spatial data in GIS when prior knowledge is available in one form or another. The availability of prior knowledge eliminates the need for time-consuming and expensive data acquisition. In addition, Bayesian methods have been widely used to process environmental data with an uncertain mixture of objective and subjective data. Dempster–Shafer uncertainty representations, which are generalizations of Bayesian approaches, are suitable for situations where there are incomplete or missing geospatial information. For spatial data, we are often faced with situations in which it is not possible to completely specify or survey certain areas. For example, sonar bathymetry surveys of the ocean floor use sonar swaths that leave gaps causing less 10% of the ocean floor to be mapped [4]. Therefore, a seafloor area which has only partial swath coverage is suitable for a Dempster–Shafer representation of such incomplete information.

In contrast to the statistical methods that predominantly model positional and measurement uncertainty, non-statistical methods are useful in situations where uncertainty cannot be measured using precise quantitative or statistical methods, but can be viewed in terms of the vagueness/ambiguities resulting from the imprecision of meaning. For these kinds of situations, we should use fuzzy set/possibility theory to model fuzziness or rough sets which work with lower- and upper-approximations of spatial data.

Many basic geographical concepts and categories do not have exact definitions and are often open to interpretation by an expert for a particular application [41]. In such situations, representing spatial information with a precise quantification would be misleading and could lead to faulty conclusions [10]. Instead, fuzzy sets can be a more realistic approach for representing this kind of geographical information. Another practical alternative is the use of rough set approaches which are based on an indiscernibility relation. This type of representation can produce a clustering using a definition of 'equivalence,' which depends on the application domain. The clustering process creates a partitioning which can increase or decrease the granularity of a spatial domain, groups geospatial items that are considered indiscernible in the application, or bin-orders spatial domains into range groups. For example, when considering the problem of map conflation in a GIS, different information sources often use distinct terms for the same spatial location or item [30]. A rough set based indiscernibility relation can be helpful in this kind of situation by indicating that different terms may actually be equivalent.

The key challenges for future research directions in GIS with uncertain spatial data are:

a. Communicating the importance of considering uncertainty in geospatial information and taking into account the cost of ignoring uncertainty in GIS applications which could lead to suboptimal conclusions and decisions.
b. Developing scientific methods for assessing data quality and assisting GIS users with evaluating error and the implications of uncertainty in geospatial data.
c. Measuring the relative sensitivity of the statistical methods with respect to the quality of the dependent variables, sampling strategy, size and type of the probability map, and the validation process used to evaluate the predictive capability of the models.
d. Developing hybrid methods for handling uncertainty by integrating the qualitative and quantitative spatial data in seamless and user-friendly frameworks.
e. Implementing spatially-explicit reliability tools and technologies for spatial sensitivity and uncertainty analysis associated with hybrid qualitative-quantitative methods.
f. Developing analytical and statistical methods for validating and measuring the effectiveness of GIS with uncertain spatial data.

An enormous amount of progress has been achieved in GIS research in recent years. Much of the published GIS applications in the past decade concern natural disasters (i.e., landslides, floods, hurricanes, tsunamis, tornadoes, earthquakes, volcanoes, wild fires, etc.) as well as man-made disasters (war, epidemics, social unrest, toxic spills, explosions, fires, etc.). On the other hand, very few studies have been published in areas such as search and rescue, intelligence, and terrorism among others. Today's GIS applications involve multiple data sets with varying levels of confidence, some precise or objective and some uncertain or subjective. New methods are needed to integrate these data sets efficiently and effectively into dynamic models.

Acknowledgements

This research is supported in part by the U.S. Naval Research Laboratory grant number N000141310505. The authors would like to thank the anonymous reviewers and the editor for their insightful comments and suggestions.

Appendix A. Bibliographical list of GIS papers with uncertain spatial data

Abbaspour, M., Mahiny, A.S., Arjmandy, R., & Naimi, B. (2011). Integrated approach for land use suitability analysis, International Agrophysics, 25(4), 311–318.

Abd Manap, M., Nampak, H., Pradhan, B., Lee, S., Sulaiman, W.N.A., & Ramli, M.F. (2014). Application of probabilistic-based frequency ratio model in groundwater potential mapping using remote sensing data and GIS, Arabian Journal of Geosciences, 7(2), 711–724.

Abdalla, R., Elawad, Y., Chen, Z., Han, S.S., & Xia, R. (2014). A GIS-supported fuzzy-set approach for flood risk assessment, Canadian Water Resources Journal, 39(1), 3–14.

Abdul Rahaman, S., Abdul Ajeez, S., Aruchamy, S., & Jegankumar, R. (2015). Prioritization of sub watershed based on morphometric characteristics using fuzzy analytical hierarchy process and geographical information system – A study of kallar watershed, Tamil Nadu, Aquatic Procedia, 4, 1322–1330.

Abdullahi, S., & Pradhan, B. (in press). Sustainable Brownfields Land Use Change Modeling Using GIS-based Weights-of-Evidence Approach, Applied Spatial Analysis and Policy, DOI 10.1007/s12061-015-9139-1.

Adab, H., Kanniah, K.D., & Solaimani, K. (2013). Modeling forest fire risk in the northeast of Iran using remote sensing and GIS techniques, Natural Hazards, 65(3), 1723–1743.

Ahadnejad, M., Maruyama, Y., & Yamazaki, F. (2009). Evaluation and forecast of human impacts based on land use changes using multi-temporal satellite imagery and GIS: A case study on Zanjan, Iran, Journal of the Indian Society of Remote Sensing, 37(4), 659–669.

Ahilan, S., O'Sullivan, J.J., Bruen, M., & Laio, F. (2012). Influences on flood frequency distributions in Irish river catchments, Hydrology and Earth System Sciences, 16(4), 1137–1150.
Akgün, A. & Bulut, F. (2007). GIS-based landslide susceptibility for Arsin-Yomra (Trabzon, North Turkey) region, Environmental Geology, 51(8), 1377–1387.
Akgün, A., & Türk, N. (2011). Mapping erosion susceptibility by a multivariate statistical method: A case study from the Ayvalık region, NW Turkey, Computers and Geosciences, 37(9), 1515–1524.
Akgun, A., Kincal, C., & Pradhan, B. (2012). Application of remote sensing data and GIS for landslide risk assessment as an environmental threat to Izmir city (west Turkey), Environmental Monitoring and Assessment, 184(9), 5453–5470.
Akgün, A., Sezer, E.A., Nefeslioglu, H.A., Gokceoglu, C., & Pradhan, B. (2012). An easy-to-use MATLAB program (MamLand) for the assessment of landslide susceptibility using a Mamdani fuzzy algorithm, Computers and Geosciences, 38(1), 23–34.
Akumu, C.E., Johnson, J.A., Etheridge, D., Uhlig, P., Woods, M., Pitt, D.G., McMurray, S. (2015). GIS-fuzzy logic based approach in modeling soil texture: Using parts of the Clay Belt and Hornepayne region in Ontario Canada as a case study, Geoderma, 239–240, 13–24.
Al-Abadi, A.M. (2015). Groundwater potential mapping at northeastern Wasit and Missan governorates, Iraq using a data-driven weights of evidence technique in framework of GIS, Environmental Earth Sciences, 74(2), 1109–1124.
Al-Ahmadi, K., Heppenstall, A., Hogg, J. & See, L. (2009). A fuzzy cellular automata urban growth model (FCAUGM) for the city of Riyadh, Saudi Arabia. Part 2: scenario testing, Applied Spatial Analysis and Policy, 2(2), 85–105.
Al-Ahmadi, K., Al-Ahmadi, S., & Al-Amri, A. (2014). Exploring the association between the occurrence of earthquakes and the geologic-tectonic variables in the Red Sea using logistic regression and GIS, Arabian Journal of Geosciences, 7(9), 3871–3879.
Alesheikh, A.A., Soltani, M.J., Nouri, N., & Khalilzadeh, M. (2008). Land assessment for flood spreading site selection using geospatial information system, International Journal of Environmental Science and Technology, 5(4), 455–462.
Alexakis, D.D., & Sarris, A. (2014). Integrated GIS and remote sensing analysis for landfill sitting in Western Crete, Greece, Environmental Earth Sciences, 72(2), 467–482.
Alexakis, D.D., Agapiou, A., Tzouvaras, M., Themistocleous, K., Neocleous, K., Michaelides, S., & Hadjimitsis, D.G. (2014). Integrated use of GIS and remote sensing for monitoring landslides in transportation pavements: the case study of Paphos area in Cyprus, Natural Hazards, 72(1), 119–141.
Al-garni, A.M. (1995). Mathematical predictive models for population estimation in urban areas using space products and GIS technology, Mathematical and Computer Modelling, 22(1), 95–107.
Aliniai, K., Yarahmadi, A., Zarin, J.Z., Yarahmadi, H., & Bakhtiari Lak, S. (in press). Parking lot site selection: An opening gate towards sustainable GIS-based urban traffic management, Journal of the Indian Society of Remote Sensing, DOI 10.1007/s12524-014-0415-3.
Allen, D.M., Schuurman, N., & Zhang, Q. (2007). Using fuzzy logic for modeling aquifer architecture, Journal of Geographical Systems Journal of Geographical Systems, 9(3), 289–310.
Al-Rafadain, Y.B.M. (2013). Using Spatial Expert Support System to Select Suitable Sites for Rain Water Harvesting, Engineering Journal, 21(4), 46–54.
Al-sharif, A.A.A. & Pradhan, B. (2014). Monitoring and predicting land use change in Tripoli Metropolitan City using an integrated Markov chain and cellular automata models in GIS, Arabian Journal of Geosciences, 7(10), 4291–4301.
Althuwaynee, O.F., Pradhan, B., & Lee, S. (2012). Application of an evidential belief function model in landslide susceptibility mapping, Computers and Geosciences, 44, 120–135.
Althuwaynee, O.F., Pradhan, B., Park, H.-J., & Lee, J.H. (2014). A novel ensemble bivariate statistical evidential belief function with knowledge-based analytical hierarchy process and multivariate statistical logistic regression for landslide susceptibility mapping, CATENA, 114, 21–36.
Amici, V., Geri, F., & Battisti, C. (2010). An integrated method to create habitat suitability models for fragmented landscapes, Journal for Nature Conservation, 18(3), 215–223.
Anane, M., Bouziri, L., Limam, A., & Jellali, S. (2012). Ranking suitable sites for irrigation with reclaimed water in the Nabeul-Hammamet region (Tunisia) using GIS and AHP-multicriteria decision analysis, Resources, Conservation and Recycling, 65, 36–46.
Anbalagan, R., Kumar, R., Lakshmanan, K., Parida, S., & Neethu, S. (in press). Landslide hazard zonation mapping using frequency ratio and fuzzy logic approach, a case study of Lachung Valley, Sikkim, Geoenvironmental Disasters, doi 10.1186/s40677-014-0009-y.
Antonakos, A.K., Voudouris, K.S., & Lambrakis, N.I. (2014). Site selection for drinking-water pumping boreholes using a fuzzy spatial decision support system in the Korinthia prefecture, SE Greece, Hydrogeology Journal, 22(8), 1763–1776.
Ardeshir, A., Mohseni, N., Behzadian, K., & Errington, M. (2014). Selection of a Bridge Construction Site Using fuzzy Analytical Hierarchy Process in Geographic Information System, Arabian Journal for Science and Engineering, 39(6), 4405–4420.
Arnous, M.O. (2011). Integrated remote sensing and GIS techniques for landslide hazard zonation: a case study Wadi Watier area, South Sinai, Egypt, Journal of Coastal Conservation, 15(4), 477–497.
Assimakopoulos, J.H., Kalivas, D.P., & Kollias, V.J. (2003). A GIS-based fuzzy classification for mapping the agricultural soils for N-fertilizers use, Science of The Total Environment, 309(1–3), 19–33.
Ayala-Carcedo, F.J., Cubillo-Nielsen, S., Domínguez, M.J., Laín, L., Ortiz, G., Alvarez, A., & Laín, R. (2003). Large Scale Rockfall Reach Susceptibility Maps in La Cabrera Sierra (Madrid) performed with GIS and Dynamic Analysis at 1:5, 000, Natural Hazards, 30(3), 325–340.

Ayalew, L., Kasahara, M., & Yamagishi, H. (2011). The spatial correlation between earthquakes and landslides in Hokkaido (Japan), a GIS-based analysis of the past and the future, Landslides, 8(4), 433–448.

Aydi, A., Zairi, M., & Ben Dhia, H. (2013). Minimization of environmental risk of landfill site using fuzzy logic, analytical hierarchy process, and weighted linear combination methodology in a geographic information system environment, Environmental Earth Sciences, 68(5), 1375–1389.

Aydin, N.Y., Kentel, E., & Duzgun, S. (2010). GIS-based environmental assessment of wind energy systems for spatial planning: A case study from Western Turkey, Renewable and Sustainable Energy Reviews, 14(1), 364–373.

Baalousha, H.M. (2010). Mapping groundwater contamination risk using GIS and groundwater modelling. A case study from the Gaza Strip, Palestine, Arabian Journal of Geosciences, 4(3–4), 483–494.

Badia, A., Serra, P., & Modugno, S. (2011). Identifying dynamics of fire ignition probabilities in two representative Mediterranean wildland-urban interface areas, Applied Geography, 31(3), 930–940.

Bai, S., Lü, G., Wang, J., Ding, L., & Zhou, P. (2011). GIS-based rare events logistic regression for landslide-susceptibility mapping of Lianyungang, China, Environmental Earth Sciences, 62(1), 139–149.

Baja, S., Chapman, D.M., & Dragovich, D. (2002). A conceptual model for defining and assessing land management units using a fuzzy modeling approach in GIS environment, Environmental Management, 29(5), 647–661.

Baja, S., Chapman, D., & Dragovich, D. (2007). Spatial based compromise programming for multiple criteria decision making in land use planning, Environmental Modeling and Assessment, 12(3), 171–184.

Balla, A., Pavlogeorgatos, G., Tsiafakis, D., & Pavlidis, G. (2013). Locating Macedonian tombs using predictive modelling, Journal of Cultural Heritage, 14(5), 403–410.

Batty, M., Xie, Y., & Sun, Z. (1999). Modeling urban dynamics through GIS-based cellular automata, Computers, Environment and Urban Systems, 23(3), 205–233.

Bekkby, T., Rinde, E., Erikstad, L., Bakkestuen, V., Longva, O., Christensen, O., Isæus, M., & Isachsen, P.E. (2008). Spatial probability modelling of eelgrass (Zostera marina) distribution on the west coast of Norway, Journal of Marine Science, 65(7), 1093–1101.

Benomar, T.B., Hu, G., & Bian, F. (2009). A predictive GIS model for potential mapping of copper, lead, and zinc in Langping area, China, Geo-spatial Information Science, 12(4), 243–250.

Beucher, A., Fröjdö, S., Österholm, P., Martinkauppi, A., & Edén, P. (2014). Fuzzy logic for acid sulfate soil mapping: Application to the southern part of the Finnish coastal areas, Geoderma, 226–227, 21–30.

Biass, S., & Bonadonna, C. (2013). A fast GIS-based risk assessment for tephra fallout: the example of Cotopaxi volcano, Ecuador: Part I: Probabilistic hazard assessment, Natural Hazards, 65(1), 477–495.

Biass, S., Frischknecht, C. & Bonadonna, C. (2013). A fast GIS-based risk assessment for tephra fallout: the example of Cotopaxi volcano, Ecuador-Part II: vulnerability and risk assessment, Natural Hazards, 64(1), 615–639.

Biass, S., Frischknecht, C. & Bonadonna, C. (2013). A fast GIS-based risk assessment for tephra fallout: the example of Cotopaxi volcano, Ecuador, Natural Hazards, 65(1), 497–521.

Binaghi, E., Luzi, L., Madella, P., Pergalani, F., & Rampini, A. (1998). Slope instability zonation: a comparison between certainty factor and fuzzy Dempster–Shafer approaches, Natural Hazards, 17(1), 77–97.

Biswas, B. (2009). Changing water resources study using GIS and spatial model - A case study of Bhatar Block, district Burdwan, West Bengal, India, Journal of the Indian Society of Remote Sensing, 37(4), 705–717.

Bojórquez-Tapia, L.A., Cruz-Bello, C.M., & Luna-González, L. (2013). Connotative land degradation mapping: A knowledge-based approach to land degradation assessment, Environmental Modelling and Software, 40, 51–64.

Bone, C., Dragicevic, S., & Roberts, A. (2005). Integrating high resolution remote sensing, GIS and fuzzy set theory for identifying susceptibility areas of forest insect infestations, International Journal of Remote Sensing, 26(21), 4809–4828.

Bone, C., Dragicevic, S., & Roberts, A. (2006). A fuzzy-constrained cellular automata model of forest insect infestations, Ecological Modelling, 192(1–2), 107–125.

Bone, C., Dragićević, S., & Roberts, A. (2007). Evaluating forest management practices using a GIS-based cellular automata modeling approach with multispectral imagery, Environmental Modeling and Assessment, 12(2), 105–118.

Boroushaki, S., &Malczewski, J. (2010). Using the fuzzy majority approach for GIS-based multicriteria group decision-making, Computers and Geosciences, 36(3), 302–312.

Brown, W., Groves, D. & Gedeon, T. (2003). Use of fuzzy membership Input layers to combine subjective geological knowledge and empirical data in a neural network method for mineral-potential mapping, Natural Resources Research, 12(3), 183–200.

Bruce, E., Albright, L., Sheehan, S., & Blewitt, M. (2014). Distribution patterns of migrating humpback whales (Megaptera novaeangliae) in Jervis Bay, Australia: A spatial analysis using geographical citizen science data, Applied Geography, 54, 83–95.

Bui, D.T., Pradhan, B., Lofman, O., Revhaug, I., & Dick, O.B. (2012a). Landslide susceptibility mapping at Hoa Binh province (Vietnam) using an adaptive neuro-fuzzy inference system and GIS, Computers and Geosciences, 45, 199–211.

Bui, D.T., Pradhan, B., Lofman, O., Revhaug, I., & Dick, O.B. (2012b). Spatial prediction of landslide hazards in Hoa Binh province (Vietnam): A comparative assessment of the efficacy of evidential belief functions and fuzzy logic models, CATENA, 96, 28–40.

Burrough, P.A., Wilson, J.P., Van Gaans, P.F.M. & Hansen, A.J. (2001). Fuzzy *k*-means classification of topo-climatic data as an aid to forest mapping in the Greater Yellowstone Area, USA, Landscape Ecology, 16(6), 523–546.

Busch, G. (2012). GIS-based tools for regional assessments and planning processes regarding potential environmental effects of poplar SRC, BioEnergy Research, 5(3), 584–605.
Canning, S. (2005). Belief' in the past: Dempster–Shafer theory, GIS and archaeological predictive modelling, Australian Archaeology, 60, 6–15
Cao, W., Zhou, S., & Wu, S. (2015). Land-use regionalization based on landscape pattern indices using rough set theory and catastrophe progression method, Environmental Earth Sciences, 73(4), 1611–1620.
Capolongo, D., Refice, A., & Mankelow, J. (2002). Evaluating earthquake-triggered landslide hazard at the basin scale through Gis in the Upper Sele River Valley, Surveys in Geophysics, 23(6), 595–625.
Carranza, E.J.M., Woldai, T., & Chikambwe, E.M. (2005). Application of data-driven evidential belief functions to prospectivity mapping for aquamarine-bearing pegmatites, Lundazi District, Zambia, Natural Resources Research, 14(1), 47–63.
Carrasco, R.M., Pedraza, J., Martin-Duque, J.F., Mattera, M., Sanz, M.A., & Bodoque, J.M. (2003). Hazard Zoning for Landslides Connected to Torrential Floods in the Jerte Valley (Spain) by using GIS Techniques, Natural Hazards, 30(3), 361–381.
Carver, S., Comber, A., McMorran, R., & Nutter, S. (2012). A GIS model for mapping spatial patterns and distribution of wild land in Scotland, Landscape and Urban Planning, 104(3–4), 395–409.
Cassel-Gintz, M., & Petschel-Held, G. (2000). GIS-based assessment of the threat to world forests by patterns of non-sustainable civilisation nature interaction, Journal of Environmental Management, 59(4), 279–298.
Ceballos-Silva, A., & López-Blanco, J. (2003). Evaluating biophysical variables to identify suitable areas for oat in Central Mexico: a multi-criteria and GIS approach, Agriculture, Ecosystems and Environment, 95(1), 371–377.
Chacón, J., Irigaray, C., Fernández, T., & El Hamdouni, R. (2006). Engineering geology maps: landslides and geographical information systems, Bulletin of Engineering Geology and the Environment, 65(4), 341–411.
Chang, S.-H., & Shiuan, W., in press, Discrete rough set analysis of two different soil-behavior-induced landslides in National Shei-Pa Park, Taiwan, Geoscience Frontiers, doi:10.1016/j.gsf.2013.12.010.
Chang, N.-B., Parvathinathan, G., & Breeden, J.B. (2008). Combining GIS with fuzzy multicriteria decision-making for landfill siting in a fast-growing urban region, Journal of Environmental Management, 87(1), 139–153.
Chang, N.-B., Chang, Y.-H., & Chen, H.-W. (2009). Fair fund distribution for a municipal incinerator using GIS-based fuzzy analytic hierarchy process, Journal of Environmental Management, 90(1), 441–454.
Charabi, Y., & Gastli, A. (2011). PV site suitability analysis using GIS-based spatial fuzzy multi-criteria evaluation, Renewable Energy, 36(9), 2554–2561.
Charnpratheep, K., Zhou, Q., & Garner, B. (1997). Preliminary landfill site screening using fuzzy geographical information systems, Waste Management and Research, 15(2), 197–215.
Chen, J., Wang, G., & Hou, C. (2005). Quantitative Prediction and Evaluation of Mineral Resources Based on GIS: A Case Study in Sanjiang Region, Southwestern China, Natural Resources Research, 14(4), 285–294.
Chen, T., Niu, R., Du, B. & Wang, Y. (2015). Landslide spatial susceptibility mapping by using GIS and remote sensing techniques: a case study in Zigui County, the Three Georges reservoir, China, Environmental Earth Sciences, 73(9), 5571–5583.
Cheng, Q., Bonham-Carter, G., Wang, W., Zhang, S., Li, W., & Qinglin, X. (2011). A spatially weighted principal component analysis for multi-element geochemical data for mapping locations of felsic intrusions in the Gejiu mineral district of Yunnan, China, Advanced Computational Geochemistry, Computers and Geosciences, 37(5), 662–669.
Choi, J.-K., Kim, K.-D., Saro Lee, & Won, J.S. (2010). Application of a fuzzy operator to susceptibility estimations of coal mine subsidence in Taebaek City, Korea, Environmental Earth Sciences, 59(5), 1009–1022.
Choi, J.-K., Oh, H.-J., Koo, B.J., Lee, S., & Ryu, J.-H. (2011). Macrobenthos habitat mapping in a tidal flat using remotely sensed data and a GIS-based probabilistic model, Marine Pollution Bulletin, 62(3), 564–572.
Choi, J.-K., Oh, H.-J., Koo, B.J., Ryu, J.-H., & Lee, S. (2011). Spatial polychaeta habitat potential mapping using probabilistic models, Estuarine, Coastal and Shelf Science, 93(2), 98–105.
Chubey, M.S., & Hathout, S. (2004). Integration of RADARSAT and GIS modelling for estimating future Red River flood risk, GeoJournal, 59(3), 237–246.
Coelho, A., Labadie, J., & Fontane, D. (2012). Multicriteria decision support system for regionalization of integrated water resources management, Water Resources Management, 26(5), 1325–1346.
Cowell, P.J., & Zeng, T.Q. (2003). Integrating uncertainty theories with GIS for modeling coastal hazards of climate change, Marine Geodesy, 26(1–2), 5–18.
Crider, K.G., Maples, E.H., & Gohlke, J.M. (2014). Incorporating Occupational Risk in Heat Stress Vulnerability Mapping, Journal of Environmental Health, 77(1), 16–22.
Dahal, R., Bhandary, N., Hasegawa, S., & Yatabe, R. (2014). Topo-stress based probabilistic model for shallow landslide susceptibility zonation in the Nepal Himalaya, Environmental Earth Sciences, 71(9), 3879–3892.
Daniel, J., & Lauffenburger, J.-P. (2012). Multi-level Dempster–Shafer Speed Limit Assistant, Belief Functions: Theory and Applications.327–334, T. Denoeux, & M-H. Masson (Eds.), Berlin, Heidelberg: Springer-Verlag
Dasgupta, A., Sastry, K.L.N., Dhinwa, P.S., Rathore, V.S., & Nathawat, M.S. (2013). Identifying desertification risk areas using fuzzy membership and geospatial technique – A case study, Kota District, Rajasthan, Journal of Earth System Science, 122 (4), 1107–1124.
Davidson, D.A., Theocharopoulos, S.P., & Bloksma, R.J. (1994). A land evaluation project in Greece using GIS and based on Boolean and fuzzy set methodologies, International Journal of Geographical Information Systems, 8(4), 369–384.

Davis, T.J., & Keller, C.P. (1997). Modelling and visualizing multiple spatial uncertainties, Computers and Geosciences, 23 (4), 397–408.
De Runz, C., Desjardin, E., Piantoni, F., & Herbin, M. (2014). Reconstruct street network from imprecise excavation data using fuzzy Hough transforms, GeoInformatica, 18(2), 253–268.
Di Martino, F., & Sessa, S. (2011). The extended fuzzy C-means algorithm for hotspots in spatio-temporal GIS, Expert Systems with Applications, 38(9), 11829–11836.
Diodato, N., & Ceccarelli, M. (2004). Multivariate indicator Kriging approach using a GIS to classify soil degradation for Mediterranean agricultural lands, Ecological Indicators, 4(3), 177–187.
Diodato, N., & Ceccarelli, M. (2006). Computational uncertainty analysis of groundwater recharge in catchment, Ecological Informatics, 1(4), 377–389.
Dixon, B. (2005a). Applicability of neuro-fuzzy techniques in predicting ground-water vulnerability: a GIS-based sensitivity analysis, Journal of Hydrology, 309, 1–4.
Dixon, B. (2005b). Groundwater vulnerability mapping: A GIS and fuzzy rule based integrated tool, Applied Geography, 25 (4), 327–347.
Djamaluddin, I., Mitani, Y., & Esaki, T. (2011). Evaluation of ground movement and damage to structures from Chinese coal mining using a new GIS coupling model, International Journal of Rock Mechanics and Mining Sciences, 48(3), 380–393.
Dlamini, W.M. (2011). Application of Bayesian networks for fire risk mapping using GIS and remote sensing data, GeoJournal, 76(3), 283–296.
Donevska, K.R., Gorsevski, P.V., Jovanovski, M., & Peševski, I. (2012). Regional non-hazardous landfill site selection by integrating fuzzy logic, AHP and geographic information systems, Environmental Earth Sciences, 67(1), 121–131.
Donglin, D., Wenjie, S. & Sha, X. (2012). Water-inrush Assessment Using a GIS-based Bayesian Network for the 12-2 Coal Seam of the Kailuan Donghuantuo Coal Mine in China, Mine Water and the Environment, 31(2), 138–146.
Dragićević, S., Lai, T., & Balram, S. (2015). GIS-based multicriteria evaluation with multiscale analysis to characterize urban landslide susceptibility in data-scarce environments, Habitat International, 45(2), 114–125.
Du, Y., Sun, Y., & Liang, F. (2012). Integrating spatial relations into case-based reasoning to solve geographic problems, Knowledge-Based Systems, 33, 111–123.
Edwards, N., Hooper, P., Knuiman, M., Foster, S., & Giles-Corti, B. (2015). Associations between park features and adolescent park use for physical activity, International Journal of Behavioral Nutrition and Physical Activity, 12(1), 1–10.
Eikaas, H.S., Kliskey, A.D., & Mcintosh, A.R. (2005). Spatial Modeling and Habitat Quantification for Two Diadromous Fish in New Zealand Streams: A GIS-Based Approach with Application for Conservation Management, Environmental Management, 36(5), 726–740.
El-Haddad, B.A., Youssef, A.M., Dhahry, B.K., & Pourghasemi, H.R. (in press). Landslide susceptibility maps using different probabilistic and bivariate statistical models and comparison of their performance at Wadi Itwad Basin, Asir Region, Saudi Arabia, Bulletin of Engineering Geology and the Environment, doi: 10.1007/s10064-015-0734-9.
Elheishy, S.S., Saleh, A.A., & Asem, A. (2013). A rough set and GIS based approach for selecting suitable shelters during an evacuation process, Journal of Geographic Information System, 5(1), 1–12.
Eskandari, S., & Chuvieco, E. (2015). Fire danger assessment in Iran based on geospatial information, International Journal of Applied Earth Observation and Geoinformation, 42, 57–64.
Feizizadeh, B., & Blaschke, T. (2013). GIS-multicriteria decision analysis for landslide susceptibility mapping: comparing three methods for the Urmia lake basin, Iran, Natural Hazards, 65(3), 2105–2128.
Feizizadeh, B., & Blaschke, T. (2014). An uncertainty and sensitivity analysis approach for GIS-based multicriteria landslide susceptibility mapping, International Journal of Geographical Information Science, 28(3), 610–638.
Feizizadeh, B., Blaschke, T., & Roodposhti, M.S. (2013). Integrating GIS based fuzzy set theory in multicriteria evaluation methods for landslide susceptibility mapping, International Journal of Geoinformatics, 9(3), 49–57.
Feizizadeh, B., Blaschke, T., & Nazmfar, H. (2014). GIS-based ordered weighted averaging and Dempster–Shafer methods for landslide susceptibility mapping in the Urmia Lake Basin, Iran, International Journal of Digital Earth, 7(8), 688–708.
Feizizadeh, B., Jankowski, P., & Blaschke, T. (2014). A GIS based spatially-explicit sensitivity and uncertainty analysis approach for multi-criteria decision analysis, Computers and Geosciences, 64, 81–95.
Feizizadeh, B., Shadman Roodposhti, M., Jankowski, P., & Blaschke, T. (2014). A GIS-based extended fuzzy multi-criteria evaluation for landslide susceptibility mapping, Computers and Geosciences, 73, 208–221.
Feng, W., Zhou, Q., Zhang, B., Zhou, W., Li, A., Zhang, H., & Xian, W. (2006). GIS-based spatial analysis and modeling for landslide hazard assessment: A case study in upper Minjiang River basin, Wuhan University Journal of Natural Sciences, 11(4), 847–852.
Feoli, E., Gallizia Vuerich, L., & Zerihun, W. (2002). Evaluation of environmental degradation in northern Ethiopia using GIS to integrate vegetation, geomorphological, erosion and socio-economic factors, Agriculture, Ecosystems and Environment, 91(1–3), 313–325.
Feoli, E., Gallizia-Vuerich, L., Ganis, P., & Woldu, Z. (2009). A classificatory approach integrating fuzzy set theory and permutation techniques for land cover analysis: A case study on a degrading area of the Rift Valley (Ethiopia). Community Ecology, 10(1), 53–64.
Ferrier, G., & Wadge, G. (1997). An integrated GIS and knowledge-based system as an aid for the geological analysis of sedimentary basins, International Journal of Geographical Information Science, 11(3), 281–297.

Filippini-Alba, J.M. & de Souza Filho, C.R. (2010). GIS-based environmental risk assessment in the Ribeira Valley, São Paulo, Brazil, Environmental Earth Sciences, 59(5), 1139–1147.
Flantua, S.G.A., Van Boxel, J.H., Hooghiemstra, H., & Van Smaalen, J. (2007). Application of GIS and logistic regression to fossil pollen data in modelling present and past spatial distribution of the Colombian savanna, Climate Dynamics, 29 (7–8), 697–712.
Fleming, G., Van der Merwe, M., & McFerren, G. (2007). Fuzzy expert systems and GIS for cholera health risk prediction in southern Africa, Environmental Modelling and Software, 22(4), 442–448.
Foody, G.M., & Boyd, D.S. (1999). Fuzzy mapping of tropical land cover along an environmental gradient from remotely sensed data with an artificial neural network, Journal of Geographical Systems, 1(1), 23–35.
Friedrich, C., Fohrer, N., & Frede, H.-G. (2002). Quantification of soil properties based on external information by means of fuzzy-set theory, Journal of Plant Nutrition and Soil Science, 165(4), 511–516.
Fustes, D., Cantorna, D., Dafonte, C., Arcay, B., Iglesias, A., & Manteiga, M. (2014). A cloud-integrated web platform for marine monitoring using GIS and remote sensing. Application to oil spill detection through SAR images, Future Generation Computer Systems, 34, 155–160.
Gahegan, M., & Flack, J. (1999). The Integration of Scene Understanding within a Geographic Information System: A Prototype Approach for Agricultural Applications, Transactions in GIS, 3(1), 31–49.
Ge, Y., Cao, F., Du, Y., Lakhan, V.C., Wang, Y., & Li, D. (2011). Application of rough set-based analysis to extract spatial relationship indicator rules: An example of land use in Pearl River Delta, Journal of Geographical Sciences, 21(1), 101–117.
Gemitzi, A., Tsihrintzis, V.A., Voudrias, E., Petalas, C., & Stravodimos, G. (2007). Combining geographic information system, multicriteria evaluation techniques and fuzzy logic in siting MSW landfills, Environmental Geology, 51(5), 797–811.
Ghayoumian, J., Mohseni Saravi, M., Feiznia, S., Nouri, B., & Malekian, A. (2007). Application of GIS techniques to determine areas most suitable for artificial groundwater recharge in a coastal aquifer in southern Iran, Journal of Asian Earth Sciences, 30(2), 364–374.
Ghinoi, A. & Chung, C.-J. (2005). STARTER: a statistical GIS-based model for the prediction of snow avalanche susceptibility using terrain features—application to Alta Val Badia, Italian Dolomites, Geomorphology, 66(1–4), 305–325.
Ghosh, S., & Carranza, E.J.M. (2010). Spatial analysis of mutual fault/fracture and slope controls on rocksliding in Darjeeling Himalaya, India, Geomorphology, 122(1–2), 1–24.
Gimpel, A., Stelzenmüller, V., Grote, B., Buck, B.H., Floeter, J., Núñez-Riboni, I., Pogoda, B., & Temming, A. (2015). A GIS modelling framework to evaluate marine spatial planning scenarios: Co-location of offshore wind farms and aquaculture in the German EEZ, Marine Policy, 55, 102–115.
Giordano, R., & Liersch, S. (2012). A fuzzy GIS-based system to integrate local and technical knowledge in soil salinity monitoring, Environmental Modelling and Software, 36, 49–63.
Giuffrida, S., Gagliano, F., & Trovato, M.R. (2014). Greenweb in land enhancement policy of Enna Province - A DRSA valuation pattern in WebGIS interaction practice, Advanced Engineering Forum, 11(1), 607–613.
Gong, G., Hargrave, K.A., Hobson, V., Spallholz, J., Boylan, M. Lefforge, D., & O'Bryant, S.E. (2011). Low-level groundwater arsenic exposure impacts cognition: A project FRONTIER study, Journal of Environmental Health, 74(2), 16–22.
González-Álvarez, I., Porwal, A., Beresford, S.W., McCuaig, T.C., & Maier, W.D. (2010). Hydrothermal Ni prospectivity analysis of Tasmania, Australia, Ore Geology Reviews, 38(3), 168–183.
Gorsevski, P.V., & Jankowski, P. (2010). An optimized solution of multi-criteria evaluation analysis of landslide susceptibility using fuzzy sets and Kalman filter, Computers and Geosciences, 36(8), 1005–1020.
Gorsevski, P.V., Gessler, P.E., & Jankowski, P. (2005). Spatial prediction of landslide hazard using fuzzy *k*-means and Dempster–Shafer theory, Transactions in GIS, 9(4), 455–474.
Gorsevski, P.V., Donevska, K.R., Mitrovski, C.D., & Frizado, J.P. (2012). Integrating multi-criteria evaluation techniques with geographic information systems for landfill site selection: A case study using ordered weighted average, Waste Management, 32(2), 287–296.
Gorsevski, P.V., Cathcart, S.C., Mirzaei, G., Jamali, M.M., Ye, X., & Gomezdelcampo, E. (2013). A group-based spatial decision support system for wind farm site selection in Northwest Ohio, Energy Policy, 55, 374–385.
Grekousis, G., Manetos, P., & Photis, Y.N. (2013). Modeling urban evolution using neural networks, fuzzy logic and GIS: The case of the Athens metropolitan area, Cities, 30, 193–203.
Guo, D., Guo, R., & Thiart, C. (2007). Predicting air pollution using fuzzy membership grade Kriging, Computers, Environment and Urban Systems, 31(1), 33–51.
Guo, E., Zhang, J., Ren, X., Zhang, Q., & Sun, Z. (2014). Integrated risk assessment of flood disaster based on improved set pair analysis and the variable fuzzy set theory in central Liaoning Province, China, Natural Hazards, 74(2), 947–965.
Guoxin, T., Shibasaki, R., & Matsumura, K. (2004). Development of a GIS-based decision support system for assessing land use status, Geo-spatial Information Science, 7(1), 72–78.
Gupta, R.P., Kanungo, D.P., Arora, M.K., & Sarkar, S. (2008). Approaches for comparative evaluation of raster GIS-based landslide susceptibility zonation maps, International Journal of Applied Earth Observation and Geoinformation, 10(3), 330–341.
Hajehforooshnia, S., Soffianian, A., Mahiny, A.S., & Fakheran, S. (2011). Multi objective land allocation (MOLA) for zoning Ghamishloo Wildlife Sanctuary in Iran, Journal for Nature Conservation, 19(4), 254–262.

Hao, L., Yang, L.-Z., & Gao, J.-M. (2014). The application of information diffusion technique in probabilistic analysis to grassland biological disasters risk, Ecological Modelling, 272, 264–270.
Harris, J.R., Wilkinson, L., Heather, K., Fumerton, S., Bernier, M.A., Ayer, J. & Dahn, R. (2001). Application of GIS Processing Techniques for Producing Mineral Prospectivity Maps—A Case Study: Mesothermal Au in the Swayze Greenstone Belt, Ontario, Canada, Natural Resources Research, 10(2), 91–124.
Hashemi, M., Alesheikh, A.A., & Zolfaghari, M.R. (2013). A spatio-temporal model for probabilistic seismic hazard zonation of Tehran, Computers and Geosciences, 58, 8–18.
He, H.S., Dey, D.C., Fan, X., Hooten, M.B., Kabrick, J.M., Wikle, C.K., & Fan, Z. (2007). Mapping pre-European settlement vegetation at fine resolutions using a hierarchical Bayesian model and GIS, Plant Ecology, 191(1), 85–94.
He, B., Chen, C., & Liu, Y. (2010). Gold resources potential assessment in eastern Kunlun Mountains of China combining weights-of-evidence model with GIS spatial analysis technique, Chinese Geographical Science, 20(5), 461–470.
Hennecke, W.G. (2004). GIS Modelling of Sea-Level Rise Induced Shoreline Changes Inside Coastal Re-Rntrants – Two Examples from Southeastern Australia, Natural Hazards, 31(1), 253–276.
Houshyar, E., SheikhDavoodi, M.J., Almassi, M., Bahrami, H., Azadi, H., Omidi, M., Sayyad, G., & Witlox, F. (2014). Silage corn production in conventional and conservation tillage systems. Part I: Sustainability analysis using combination of GIS/AHP and multi-fuzzy modeling, Ecological Indicators, 39, 102–114.
Hu, Y., Wang, J., Zhu, J., & Ren, D. (2011). Mapping under-five mortality in the Wenchuan earthquake using hierarchical Bayesian modeling, International Journal of Environmental Health Research, 21(5), 364–371.
Huang, Q.-H., & Cai, Y.-L. (2007). Simulation of land use change using GIS-based stochastic model: the case study of Shiqian County, Southwestern China, Stochastic Environmental Research and Risk Assessment, 21(4), 419–426.
Huang, Q.-H., Cai, Y.-L., & Peng, J. (2007). Modeling the spatial pattern of farmland using GIS and multiple logistic regression: a case study of Maotiao River Basin, Guizhou Province, China, Environmental Modeling and Assessment, 12(1), 55–61.
Huang, Z., Brooke, B.P., & Harris, P.T. (2011). A new approach to mapping marine benthic habitats using physical environmental data, Continental Shelf Research, 31(2), S4-S16.
Ilanloo, M. (2011). A comparative study of fuzzy logic approach for landslide susceptibility mapping using GIS: An experience of Karaj dam basin in Iran, Procedia - Social and Behavioral Sciences, 19, 668–676.
Jalayer, F., De Risi, R., De Paola, F., Giugni, M., Manfredi, G., Gasparini, P., Topa, M.E., Yonas, N., Yeshitela, K., Nebebe, A., Cavan, G., Lindley, S., Printz, A., & Renner, F. (2014). Probabilistic GIS-based method for delineation of urban flooding risk hotspots, Natural Hazards, 73(2), 975–1001.
Jasiewicz, J. (2011). A new GRASS GIS fuzzy inference system for massive data analysis, Computers and Geosciences, 37 (9), 1525–1531
Jebur, M.N., Pradhan, B., Shafri, H.Z.M., Yusoff, Z.M., & Tehrany, M.S. (2015). An integrated user-friendly ArcMAP tool for bivariate statistical modelling in geoscience applications, Geoscientific Model Development, 8(3), 881–891.
Jeong, J.S., García-Moruno, L., & Hernández-Blanco, J. (2013). A site planning approach for rural buildings into a landscape using a spatial multi-criteria decision analysis methodology, Land Use Policy, 32, 108–118.
Jiao, S., Gao, Q., Wei, C.-Y., Liu, B., Li, X.-D., Zeng, G.-M., Yuan, Z.-X., & Liang, J. (2012). Ecological suitability evaluation for urban growth boundary in red soil hilly areas based on fuzzy theory, Journal of Central South University, 19(5), 1364–1369.
Jie, Y., Shaohong, W., & Erfu, D. (2012). Assessment of Economic Damage Risks from Typhoon Disasters in Guangdong, China, Journal of Resources and Ecology, 3(2), 144–150.
Joerin, F., & Musy, A. (2000). Land management with GIS and multicriteria analysis, International Transactions in Operational Research, 7(1), 67–78.
Jordan, C., Zhang, C., & Higgins, A. (2007). Using GIS and statistics to study influences of geology on probability features of surface soil geochemistry in Northern Ireland, Journal of Geochemical Exploration, 93(3), 135–152.
Jung, Y.H., & Merwade, V. (2012). Uncertainty quantification in flood inundation mapping using generalized likelihood uncertainty estimate and sensitivity analysis, Journal of Hydrologic Engineering, 17(4), 507–520.
Kalantari, Z., Nickman, A., Lyon, S.W., Olofsson, B., & Folkeson, L. (2014). A method for mapping flood hazard along roads, Journal of Environmental Management, 133, 69–77.
Kanungo, D.P., Arora, M.K., Sarkar, S., & Gupta, R.P. (2006). A comparative study of conventional, ANN black box, fuzzy and combined neural and fuzzy weighting procedures for landslide susceptibility zonation in Darjeeling Himalayas, Engineering Geology, 85(3–4), 347–366.
Kanungo, D.P., Arora, M.K., Sarkar, S., & Gupta, R.P. (2009). A fuzzy set based approach for integration of thematic maps for landslide susceptibility zonation, Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards, 3(1), 30–43.
Kayastha, P. (2012). Application of fuzzy logic approach for landslide susceptibility mapping in Garuwa sub-basin, East Nepal, Frontiers of Earth Science, 6(4), 420–432.
Khamespanah, F., Delavar, M.R., Samadi Alinia, H., & Zare, M. (2013). Granular computing and Dempster–Shafer integration in seismic vulnerability assessment, Intelligent Systems for Crisis Management.147–158, S. Zlatanova, R. Peters, A. Dilo, & H. Scholten (Eds.), Berlin, Heidelberg: Springer-Verlag

Khan, A., Khan, H.H., Umar, R. & Khan, M.H. (2014). An integrated approach for aquifer vulnerability mapping using GIS and rough sets: study from an alluvial aquifer in North India, Hydrogeology Journal, 22(7), 1561–1572.
Khoi, D.D., & Murayama, Y. (2010). Delineation of suitable cropland areas using a GIS based multi-criteria evaluation approach in the tam Dao national park region, Vietnam, Sustainability, 2(7), 2024–2043.
Kiavarz Moghaddam, M., Samadzadegan, F., Noorollahi, Y., Sharifi, M.A., & Itoi, R. (2014). Spatial analysis and multi-criteria decision making for regional-scale geothermal favorability map, Geothermics, 50, 189–201.
Kim, K.-D., Oh, H.-J., Choi, J.-K., Won, J.-S., & Lee, S. (2006). Assessment of ground subsidence hazard near an abandoned underground coal mine using GIS, Environmental Geology, 50(8), 1183–1191.
Kirschbaum, D., Stanley, T., & Yatheendradas S., in press, Modeling landslide susceptibility over large regions with fuzzy overlay, Landslides, doi 10.1007/s10346-015-0577-2.
Klingseisen, B., Metternicht, G., & Paulus, G. (2008). Geomorphometric landscape analysis using a semi-automated GIS-approach, Environmental Modelling and Software, 23(1), 109–121.
Ko, Y., Lee, S., Kim, J., Kim, K.-H., & Jung, M.-S. (2006). Relationship between mn nodule abundance and other geological factors in the northeastern pacific: Application of gis and probability method, Ocean Science Journal, 41(3), 149–161.
Kocabas, V. & Dragicevic, S. (2013). Bayesian networks and agent-based modeling approach for urban land-use and population density change: a BNAS model, Journal of Geographical Systems, 15(4), 403–426.
Kollias, V.J., & Kalivas, D.P. (1998). The enhancement of a commercial geographical information system (ARC/INFO) with fuzzy processing capabilities for the evaluation of land resources, Computers and Electronics in Agriculture, 20(1), 79–95.
Kollias, V.J., Kalivas, D.P., & Yassoglou, N.J. (1999). Mapping the soil resources of a recent alluvial plain in Greece using fuzzy sets in a GIS environment, European Journal of Soil Science, 50(2), 261–273.
Kontoes, C., Wilkinson, G.G., Burrill, A., Goffredo, S., & Mégier, J. (1993). An experimental system for the integration of GIS data in knowledge-based image analysis for remote sensing of agriculture, International Journal of Geographical Information Science, 7(3), 247–262.
Kordi, M., & Anders Brandt, S. (2012). Effects of increasing fuzziness on analytic hierarchy process for spatial multicriteria decision analysis, Computers, Environment and Urban Systems, 36(1), 43–53.
Kritikos, T. & Davies, T. (in press). Assessment of rainfall-generated shallow landslide/debris-flow susceptibility and run-out using a GIS-based approach: application to western Southern Alps of New Zealand, Landslides, doi 10.1007/s10346-014-0533-6.
Kühmaier, M., Kanzian, C., & Stampfer, K. (2014). Identification of potential energy wood terminal locations using a spatial multicriteria decision analysis, Biomass and Bioenergy, 66, 337–347.
Kumar, R., & Anbalagan, R. (2015). Landslide susceptibility zonation in part of Tehri reservoir region using frequency ratio, fuzzy logic and GIS, Journal of Earth System Science, 124(2), 431–448.
Kundu, S., Pant, C.C., Sharma, D.C., & Saha, A.K. (2013). Remote Sensing and GIS Based Landslide Susceptibility Assessment using Binary Logistic Regression Model: A Case Study in the Ganeshganga Watershed, Himalayas, Journal of the Indian Society of Remote Sensing, 41(3), 697–709.
Lagacherie, P., Cazemier, D.R., Martin-Clouaire, R., & Wassenaar, T. (2000). A spatial approach using imprecise soil data for modelling crop yields over vast areas, Agriculture, Ecosystems and Environment, 81(1), 5–16.
Lai, C., Chen, X., Chen, X., Wang, Z., Wu, X., & Zhao, S. (2015). A fuzzy comprehensive evaluation model for flood risk based on the combination weight of game theory, Natural Hazards, 77(2), 1243–1259.
Lamelas, M. T., Marinoni, O., Hoppe, A., & De la Riva, J. (2008). Doline probability map using logistic regression and GIS technology in the central Ebro Basin (Spain), Environmental Geology, 54(5), 963–977.
Lark, R.M., & Bolam, H.C. (1997). Uncertainty in prediction and interpretation of spatially variable data on soils, Geoderma, 77(2–4), 263–282.
Lee, S., & Choi, U. (2003). Development of GIS-based geological hazard information system and its application for landslide analysis in Korea, Geosciences Journal, 7(3), 243–252.
Lee, S. (2004). Application of Likelihood Ratio and Logistic Regression Models to Landslide Susceptibility Mapping Using GIS, Environmental Management, 34(2), 223–232.
Lee, S., Choi, J., & Min, K. (2002). Landslide susceptibility analysis and verification using the Bayesian probability model, Environmental Geology, 43(1–2), 120–131.
Lee, S., Hwang, J., & Park, I. (2013). Application of data-driven evidential belief functions to landslide susceptibility mapping in Jinbu, Korea, CATENA, 100, 15–30.
Lee, S.-T., Wu, C.-W., & Lei, T.-C. (2013). CA-GIS model for dynamic simulation of commercial activity development by the combination of ANN and Bayesian probability, Procedia Computer Science, 18, 651–660.
Lee, M.-J., Song, W.-K., Won, J.-S., Park, I., & Lee, S. (2014). Spatial and temporal change in landslide hazard by future climate change scenarios using probabilistic-based frequency ratio model, Geocarto International, 29(6), 639–662.
Lee, M.-J., Park, I. & Lee, S. (2015). Forecasting and validation of landslide susceptibility using an integration of frequency ratio and neuro-fuzzy models: a case study of Seorak mountain area in Korea, Environmental Earth Sciences, 74(1), 413–429.
Lei, T.C., Wan, S., & Chou, T.Y. (2008). The comparison of PCA and discrete rough set for feature extraction of remote sensing image classification – A case study on rice classification, Taiwan, Computational Geosciences, 12(1), 1–14.

Leung, Y., Fung, T., Mi, J.-S., & Wu, W.-Z. (2007). A rough set approach to the discovery of classification rules in spatial data, International Journal of Geographical Information Science, 21(9), 1033–1058.

Lewis, S.M., Fitts, G., Kelly, M., & Dale, L. (2014). A fuzzy logic-based spatial suitability model for drought-tolerant switchgrass in the United States, Computers and Electronics in Agriculture, 103, 39–47.

Li, J., Jiang, J.-H., & Li, M.-H. (2001). Hazard analysis system of urban post-earthquake fire based on GIS, Acta Seismologica Sinica, 14(4), 448–455.

Li, C., Ma, T., & Zhu, X. (2010). aiNet- and GIS-based regional prediction system for the spatial and temporal probability of rainfall-triggered landslides, Natural Hazards, 52(1), 57–78.

Li, Y., Li, C.-k., Tao, J.-j., & Wang, L.-d. (2011). Study on Spatial Distribution of Soil Heavy Metals in Huizhou City Based on BP--ANN Modeling and GIS, Procedia Environmental Sciences, 10, 1953–1960.

Li, Y., Aydin, A.; Xiang, X., Ju, N., Zhao, J., & Ozbek, A. (2012). Landslide susceptibility mapping and evaluation along a river valley in China, Acta Geologica Sinica, 86(4), 1022–1030.

Li, L., Tang, J., & Liu, Y. (2015). Partial discharge recognition in gas insulated switchgear based on multi-information fusion, IEEE Transactions on Dielectrics and Electrical Insulation, 22(2), 1080–1087.

Likkason, O.K., Shemang, E.M., & Suh, C.E. (1997). The application of evidential belief function in the integration of regional geochemical and geological data over the Ife-Ilesha goldfield, Nigeria, Journal of African Earth Sciences, 25(3), 491–501.

Lin, C.T., & Lin, J.K. (2013). Fuzzy-GIS approach for applying the AHP multi-criteria decision-making model to evaluate real estate purchases, Journal of Testing and Evaluation, 41(6), 978–989.

Lisitsin, V.A., Porwal, A., & McCuaig, T.C. (2014). Probabilistic fuzzy Logic modeling: quantifying uncertainty of mineral prospectivity models Using Monte Carlo Simulations, Mathematical Geosciences, 46(6), 747–769.

Lister, T.W., Lister, A.J., & Alexander, E. (2014). Land use change monitoring in Maryland using a probabilistic sample and rapid photointerpretation, Applied Geography, 51, 1–5.

Liu, Y., & Phinn, S.R. (2003). Modelling urban development with cellular automata incorporating fuzzy-set approaches, Environment and Urban Systems, 27(6), 637–658.

Liu, Y. (2012). Modelling sustainable urban growth in a rapidly urbanising region using a fuzzy-constrained cellular automata approach, International Journal of Geographical Information Science, 26(1), 151–167.

Liu, L., Jing, X., Wang, J., & Zhao, C. (2009). Analysis of the changes of vegetation coverage of western Beijing mountainous areas using remote sensing and GIS, Environmental Monitoring and Assessment, 153(1–4), 339–349.

Liu, D., Li, B., Liu, X., & Warrington, D.N. (2011). Monitoring land use change at a small watershed scale on the Loess Plateau, China: applications of landscape metrics, remote sensing and GIS, Environmental Earth Sciences, 64(8), 2229–2239.

Liu, X.-P., Zhang, J.-Q., Tong, Z.-J., & Bao, Y. (2012). GIS-based multi-dimensional risk assessment of the grassland fire in northern China, Natural Hazards, 64(1), 381–395.

Liu, C., Sun, J., & Liu, Y. (2013). Evaluation on engineering geology applicability for urban construction land based on GIS: Taking zhengding new district of shijiazhuang city for example, Advanced Materials Research, 671–674, 35–38, Y. Huang, T. Bao, & H. Wang (Eds.), Dürnten, Switzerland: Trans Tech Publications.

Liu, Y., Cheng, Q., Xia, Q., & Wang, X. (2015). The use of evidential belief functions for mineral potential mapping in the Nanling belt, South China, Frontiers of Earth Science, 9(2), 342–354.

Lorz, C., Fürst, C., Galic, Z., Matijasic, D., Podrazky, V., Potocic, N., Simoncic, P., Strauch, M., Vacik, H., & Makeschin, F. (2010). GIS-based Probability Assessment of Natural Hazards in Forested Landscapes of Central and South-Eastern Europe, Environmental Management, 46(6), 920–930.

Lu, C.Y., Gu, W., Dai, A.H., & Wei, H.Y. (2012). Assessing habitat suitability based on geographic information system (GIS) and fuzzy: A case study of Schisandra sphenanthera Rehd. et Wils. in Qinling Mountains, China, Ecological Modelling, 242, 105–115.

Lu, F., Chen, Z., & Liu, W. (2014). A Gis-based system for assessing marine water quality around offshore platforms, Ocean and Coastal Management, 102, 294–306.

Lucas, C. (2012). Multi-criteria modelling and clustering of spatial information, International Journal of Geographical Information Science, 26(10), 1897–1915.

Ludwig, R., Probeck, M., & Mauser, W. (2003). Mesoscale water balance modelling in the Upper Danube watershed using sub-scale land cover information derived from NOAA-AVHRR imagery and GIS-techniques, Physics and Chemistry of the Earth, Parts A/B/C, 28(33–36), 1351–1364.

Ma, S., Feng, J., & Cao, H. (2006). Fuzzy model of regional economic competitiveness in GIS spatial analysis: Case study of Gansu, Western China, Fuzzy Optimization and Decision Making, 5(2), 99–111.

Magesh, N.S., Chandrasekar, N., & Kaliraj, S. (2015). Mapping of heavy mineral placers through marine GIS expert system: a case study in Kalaignanapuram coastal stretch, southeast coast of Tamil Nadu, India, Arabian Journal of Geosciences, 8 (1), 195–206.

Magliulo, P., Di Lisio, A., Russo, F., & Zelano, A. (2008). Geomorphology and landslide susceptibility assessment using GIS and bivariate statistics: a case study in southern Italy, Natural Hazards, 47(3), 411–435.

Maina, J., Venus, V., McClanahan, T.R., & Ateweberhan, M. (2008). Modelling susceptibility of coral reefs to environmental stress using remote sensing data and GIS models, Ecological Modelling, 212(3–4), 180–199.

Malczewski, J. & Rinner, C. (2005). Exploring multicriteria decision strategies in GIS with linguistic quantifiers: A case study of residential quality evaluation, Journal of Geographical Systems, 7(2), 249–268.
Malczewski, J. (2006). Ordered weighted averaging with fuzzy quantifiers: GIS-based multicriteria evaluation for land-use suitability analysis, International Journal of Applied Earth Observation and Geoinformation, 8(4), 270–277.
Malekmohammadi, B., Mehrian, M.R., & Jafari, H.R. (2012). Site selection for managed aquifer recharge using fuzzy rules: integrating geographical information system (GIS) tools and multi-criteria decision making, Hydrogeology Journal, 20(7), 1393–1405.
Malinowska, A. (2011). A. Malinowska, A fuzzy inference-based approach for building damage risk assessment on mining terrains, Engineering Structures, 33(1), 163–170.
Malins, D., & Metternicht, G. (2006). Assessing the spatial extent of dryland salinity through fuzzy modeling, Ecological Modelling, 193(3–4), 387–411.
March, D., Alós, J., Cabanellas-Reboredo, M., Infantes, E., & Palmer, M. (2013). Probabilistic mapping of Posidonia oceanica cover: A Bayesian geostatistical analysis of seabed images, Aquatic Botany, 106, 14–19.
Marquínez, J., Menéndez Duarte, R., Farias, P., & Jiménez Sánchez, M. (2003). Predictive GIS-Based Model of Rockfall Activity in Mountain Cliffs, Natural Hazards, 30(3), 341–360.
Martin-Clouaire, R., Cazemier, D.R., & Lagacherie, P. (2000). Representing and processing uncertain soil information for mapping soil hydrological properties, Computers and Electronics in Agriculture, 29(1), 41–57.
Massei, G., Rocchi, L., Paolotti, L., Greco, S., & Boggia, A. (2014). Decision Support Systems for environmental management: A case study on wastewater from agriculture, Journal of Environmental Management, 146, 491–504.
Meinhardt, M., Fink, M., & Tünschel, H. (2015). Landslide susceptibility analysis in central Vietnam based on an incomplete landslide inventory: Comparison of a new method to calculate weighting factors by means of bivariate statistics, Geomorphology, 234, 80–97.
Metternicht, G., & Gonzalez, S. (2005). FUERO: foundations of a fuzzy exploratory model for soil erosion hazard prediction, Environmental Modelling and Software, 20(6), 715–728.
Metternicht, G. (2001). Assessing temporal and spatial changes of salinity using fuzzy logic, remote sensing and GIS, Foundations of an expert system, Ecological Modelling, 144(2–3), 163–179.
Mihai, B., Sandric, I., Savulescu, I., & Chitu, Z. (2010). Detailed mapping of landslide susceptibility for urban planning purposes in carpathian and subcarpathian towns of Romania, Cartography in Central and Eastern Europe.417–429, G. Gartner, & F. Ortag, Felix (Eds.), Berlin, Heidelberg: Springer-Verlag
Mitra, B., Scott, H.D., Dixon, J.C., & McKimmey, J.M. (1998). Applications of fuzzy logic to the prediction of soil erosion in a large watershed, Geoderma, 86(3–4), 183–209.
Mogaji, K.A., Lim, H.S., & Abdullah, K. (2015). Regional prediction of groundwater potential mapping in a multifaceted geology terrain using GIS-based Dempster–Shafer model, Arabian Journal of Geosciences, 8(5), 3235–3258.
Mohammadi, K., Niknam, R. & Majd, V.J. (2009). Aquifer vulnerability assessment using GIS and fuzzy system: a case study in Tehran–Karaj aquifer, Iran, Environmental Geology, 58(2), 437–446.
Mohammadi, F., Pir Bavaghar, M., & Shabanian, N. (2014). Forest Fire Risk Zone Modeling Using Logistic Regression and GIS: An Iranian Case Study, Small-scale Forestry, 13(1), 117–125.
Mohammady, M., Pourghasemi, H.R., & Pradhan, B. (2012). Landslide susceptibility mapping at Golestan Province, Iran: A comparison between frequency ratio, Dempster–Shafer, and weights-of-evidence models, Journal of Asian Earth Sciences, 61, 221–236.
Mosadeghi, R., Warnken, J., Tomlinson, R., & Mirfenderesk, H. (2015). Comparison of fuzzy-AHP and AHP in a spatial multi-criteria decision making model for urban land-use planning, Computers, Environment and Urban Systems, 49, 54–65.
Mousavi, S.Z., Kavian, A., Soleimani, K., Mousavi, R., & Shirzadi, A. (2011). GIS-based spatial prediction of landslide susceptibility using logistic regression model, Geomatics, Natural Hazards and Risk, 2(1), 33–50.
Mousavi, M., Hesari, M., & Azarbakht, A. (2014). Seismic risk assessment of the 3rd Azerbaijan gas pipeline in Iran, Natural Hazards, 74(3), 1327–1348.
Münch, Z. & Conrad, J. (2007). Remote sensing and GIS based determination of groundwater dependent ecosystems in the Western Cape, South Africa, Hydrogeology Journal, 15(1), 19–28.
Nachbaur, A., & Rohmer, J. (2011). Managing expert-information uncertainties for assessing collapse susceptibility of abandoned underground structures, Engineering Geology, 123(3), 166–178.
Nampak, H., Pradhan, B., & Manap, M.A. (2014). Application of GIS based data driven evidential belief function model to predict groundwater potential zonation, Journal of Hydrology, 513, 283–300.
Nasserabadi, H.D., Shahabi, H., Keihanfard, S., Mashahi, D.R., & Khodakarami, M. (2013). Application of fuzzy set theory and SPOT satellite images in site selection of public libraries (case study: Saqqez city, Iran), Research Journal of Applied Sciences, Engineering and Technology, 6(6), 122–1128.
Nath, S.K. (2004). Seismic Hazard Mapping and Microzonation in the Sikkim Himalaya through GIS Integration of Site Effects and Strong Ground Motion Attributes, Natural Hazards, 31(2), 319–342.
Navas, J.M., Telfer, T.C., & Ross, L.G. (2011). Spatial modeling of environmental vulnerability of marine finfish aquaculture using GIS-based neuro-fuzzy techniques, Marine Pollution Bulletin, 62(8), 1786–1799.

Navas, J.M., Telfer, T.C., & Ross, L.G. (2012). Separability indexes and accuracy of neuro-fuzzy classification in Geographic Information Systems for assessment of coastal environmental vulnerability, Ecological Informatics, 12, 43–49.
Nelson, E.P., Connors, K.A., & Suárez S., C. (2007). GIS-based slope stability analysis, Chuquicamata open pit copper mine, Chile, Natural Resources Research, 16(2), 171–190.
Neshat, A., & Pradhan, B. (in press). Risk assessment of groundwater pollution with a new methodological framework: application of Dempster–Shafer theory and GIS, Natural Hazards, doi 10.1007/s11069-015-1788-5.
Neshat, A., Pradhan, B., & Javadi, S. (2015). Risk assessment of groundwater pollution using Monte Carlo approach in an agricultural region: An example from Kerman Plain, Iran, Computers, Environment and Urban Systems, 50, 66–73.
Neuhäuser, B., Damm, B., & Terhorst, B. (2012). GIS-based assessment of landslide susceptibility on the base of the Weights-of-Evidence model, Landslides, 9(4), 511–528.
Nguyen, T.T., Verdoodt, A., Van Y, T., Delbecque, N., Tran, T.C., & Van Ranst, E. (2015). Design of a GIS and multi-criteria based land evaluation procedure for sustainable land-use planning at the regional level, Agriculture, Ecosystems and Environment, 200, 1–11.
Ning, S.-K., & Chang, N.-B. (2004). Optimal expansion of water quality monitoring network by fuzzy optimization approach, Environmental Monitoring and Assessment, 91(1–3), 145–170.
Nisar Ahamed, T.R., Gopal Rao, K., & Murthy, J.S.R. (2000a). GIS-based fuzzy membership model for crop-land suitability analysis, Agricultural Systems, 63(2), 75–95.
Nisar Ahamed, T.R., Gopal Rao, K., & Murthy, J.S.R. (2000b). Fuzzy class membership approach to soil erosion modelling, Agricultural Systems, 63(2), 97–110.
Nobre, R.C.M., Rotunno Filho, O.C., Mansur, W.J., Nobre, M.M.M., & Cosenza, C.A.N. (2007). Groundwater vulnerability and risk mapping using GIS, modeling and a fuzzy logic tool, Journal of Contaminant Hydrology, 94(3–4), 277–292.
Nourqolipour, R., Mohamed Shariff, A.R.B., Balasundram, S.K., Ahmad, N., Sood, A.M., Buyong, T., & Amiri, F. (2015). A GIS-based model to analyze the spatial and temporal development of oil palm land use in Kuala Langat district, Malaysia, Environmental Earth Sciences, 73(4), 1687–1700.
Nurmiaty, B.S. (2014). Using fuzzy set approaches in a raster GIS for land suitability assessment at a regional scale: Case study in maros region, Indonesia, Canadian Center of Science and Education, 8(3), 115–125.
Ocalir, E.V., Ercoskun, O.Y., & Tur, R. (2010). An integrated model of GIS and fuzzy logic (FMOTS) for location decisions of taxicab stands, Expert Systems with Applications, 37(7), 4892–4901.
Ogburn, D.E. (2006). Assessing the level of visibility of cultural objects in past landscapes, Journal of Archaeological Science, 33(3), 405–413.
Oh, K., & Jeong, Y. (2002). The usefulness of the GIS—fuzzy set approach in evaluating the urban residential environment, Environment and Planning B: Planning and Design, 29(4), 589–606.
Oh, H.-J., & Lee, S. (2011). Cross-application used to validate landslide susceptibility maps using a probabilistic model from Korea, Environmental Earth Sciences, 64(2), 395–409.
Oh, H.-J., & Pradhan, B. (2011). Application of a neuro-fuzzy model to landslide-susceptibility mapping for shallow landslides in a tropical hilly area, Computers and Geosciences, 37(9), 1264–1276.
Oh, H.-J., Ahn, S.-C., Choi, J.-K., & Lee, S. (2011). Sensitivity analysis for the GIS-based mapping of the ground subsidence hazard near abandoned underground coal mines, Environmental Earth Sciences, 64(2), 347–358.
Osna, T., Sezer, E.A., & Akgün, A. (2014). GeoFIS: An integrated tool for the assessment of landslide susceptibility, Computers and Geosciences, 66, 20–30.
Ozdemir, A. (2009). Landslide susceptibility mapping of vicinity of Yaka Landslide (Gelendost, Turkey) using conditional probability approach in GIS, Environmental Geology, 57(7), 1675–1686.
Park, N.-W. (2011). Application of Dempster–Shafer theory of evidence to GIS-based landslide susceptibility analysis, Environmental Earth Sciences, 62(2), 367–376.
Park, I., Choi, J., Lee, M.J., & Lee, S. (2012). Application of an adaptive neuro-fuzzy inference system to ground subsidence hazard mapping, Computers and Geosciences, 48, 228–238.
Park, H.J., Lee, J.H., & Woo, I. (2013). Assessment of rainfall-induced shallow landslide susceptibility using a GIS-based probabilistic approach, Engineering Geology, 161, 1–15.
Park, I., Lee, J., &, Saro, L. (2014). Ensemble of ground subsidence hazard maps using fuzzy logic, Central European Journal of Geosciences, 6(2), 207–218.
Parry, G.S., Bodger, O., McDonald, R.A., & Forman, D.W. (2013). A systematic re-sampling approach to assess the probability of detecting otters Lutra lutra using spraint surveys on small lowland rivers, Ecological Informatics, 14, 64–70.
Pászto, V., Brychtová, A., Tu?ek, P., Marek, L., & Burian, J. (2015). Using a fuzzy inference system to delimit rural and urban municipalities in the Czech Republic in 2010, Journal of Maps, 11(2), 231–239.
Pathak, D.R., & Hiratsuka, A. (2011). An integrated GIS based fuzzy pattern recognition model to compute groundwater vulnerability index for decision making, Journal of Hydro-environment Research, 5(1), 63–77.
Pawlin Vasanthi, J., Brindha, B., Vidhyalakshmi, R., Devi Marimuthu, P., & Balasubramanian, S. (2015). Probability Mapping to Determine the Spatial Risk Pattern of Acute Gastroenteritis in Coimbatore District, India, Using Geographic Information Systems (GIS), Indian Journal of Community Medicine, 40(3), 188–192.
Peled, A., & Gilichinsky, M. (2013). GIS-driven classification of land use using IKONOS data and a core national spatial information database, Applied Geomatics, 5(2), 109–117.

Peng, W. (1998). Synthetic Analysis for Extracting Information on Soil Salinity Using Remote Sensing and GIS: A Case Study of Yanggao Basin in China, Environmental Management, 22(1), 153–159.

Peng, L., Niu, R.Q, Huang, B., Wu, X.L., Zhao, Y.N., &Ye, R.Q. (2014). Landslide susceptibility mapping based on rough set theory and support vector machines: A case of the Three Gorges area, China, Geomorphology, 204, 287–301.

Perakis, K.G., & Moysiadis, A.K. (2011). Geospatial predictive modelling of the Neolithic archaeological sites of Magnesia in Greece, International Journal of Digital Earth, 4(5), 421–433.

Pezeshki, Z., Tafazzoli-Shadpour, M., Mansourian, A., Eshrati, B., Omidi, E., & Nejadqoli, I. (2012). Model of cholera dissemination using geographic information systems and fuzzy clustering means: Case study, Chabahar, Iran, Public Health, 126(10), 881–887.

Plewe, B.S. (2003). Representing datum-level uncertainty in historical GIS, Cartography and Geographic Information Science, 30(4), 319–334.

Pollak, K., Peled, A., & Hakkert, S. (2014). Geo-Based Statistical Models for Vulnerability Prediction of Highway Network Segments, ISPRS International Journal of Geo-Information, 3(2), 619–637.

Pourghasemi, H.R., Mohammady, M., & Pradhan, B. (2012). Landslide susceptibility mapping using index of entropy and conditional probability models in GIS: Safarood Basin, Iran, CATENA, 97, 71–84.

Pourghasemi, H., Pradhan, B., Gokceoglu, C., & Moezzi, K.D. (2013). A comparative assessment of prediction capabilities of Dempster–Shafer and Weights-of-evidence models in landslide susceptibility mapping using GIS, Geomatics, Natural Hazards and Risk, 4(2), 93–118.

Pourghasemi, H.R., Jirandeh, A.G., Pradhan, B., Xu, C., & Gokceoglu, C. (2013). Landslide susceptibility mapping using support vector machine and GIS at the Golestan Province, Iran, Journal of Earth System Science, 122(2), 349–369.

Pourghasemi, H.R., Moradi, H.R., Aghda, S.M.F., Gokceoglu, C., & Pradhan, B. (2014). GIS-based landslide susceptibility mapping with probabilistic likelihood ratio and spatial multi-criteria evaluation models (North of Tehran, Iran), Arabian Journal of Geosciences, 7(5), 1857–1878.

Pourghasemi, H.R., Moradi, H.R., Fatemi Aghda, S.M., Gokceoglu, C., & Pradhan, B. (2014). GIS-based landslide susceptibility mapping with probabilistic likelihood ratio and spatial multi-criteria evaluation models (North of Tehran, Iran), Arabian Journal of Geosciences, 7(5), 1857–1878.

Pourtaghi, Z.S., & Pourghasemi, H.R. (2014). GIS-based groundwater spring potential assessment and mapping in the Birjand Township, southern Khorasan Province, Iran, Hydrogeology Journal, 22(3), 643–662.

Pradhan, B. (2010). Landslide susceptibility mapping of a catchment area using frequency ratio, fuzzy logic and multivariate logistic regression approaches, Journal of the Indian Society of Remote Sensing, 38(2), 301–320.

Pradhan, B. (2013). A comparative study on the predictive ability of the decision tree, support vector machine and neuro-fuzzy models in landslide susceptibility mapping using GIS, Computers and Geosciences, 51, 350–365.

Pradhan, B., Lee, S., & Buchroithner, M.F. (2009). Use of geospatial data and fuzzy algebraic operators to landslide-hazard mapping, Applied Geomatics, 1(1–2), 3–15.

Pradhan, B., Abokharima, M.H., Jebur, M.N., & Tehrany, M.S. (2014). Land subsidence susceptibility mapping at Kinta Valley (Malaysia) using the evidential belief function model in GIS, Natural Hazards, 73(2), 1019–1042.

Prasannakumar, V., & Vijith, H. (2012). Evaluation and validation of landslide spatial susceptibility in the Western Ghats of Kerala, through GIS-based Weights of Evidence model and Area Under Curve technique, Journal of the Geological Society of India, 80(4), 515–523.

Qi, F., Zhu, A.-X., Harrower, M., Burt, J.E. (2006). Fuzzy soil mapping based on prototype category theory, Geoderma, 136 (3–4), 774–787

Qi, H.H., Qi, P., & Altinakar, M.S. (2013). GIS-Based Spatial Monte Carlo Analysis for Integrated Flood Management with Two Dimensional Flood Simulation, Water Resources Management, 27(1), 3631–3645.

Qiu, F., Chastain, B., Zhou, Y., Zhang, C., & Sridharan, H. (2014). Modeling land suitability/capability using fuzzy evaluation, GeoJournal, 79(2), 167–182.

Rahman, M.R., Shi, Z.H. & Chongfa, C. (2014). Assessing regional environmental quality by integrated use of remote sensing, GIS, and spatial multi-criteria evaluation for prioritization of environmental restoration, Environmental Monitoring and Assessment, 186(11), 6993–7009.

Rahman, M.R., Shi, Z.H., Chongfa, C., & Dun, Z. (in press). Assessing soil erosion hazard -a raster based GIS approach with spatial principal component analysis (SPCA). Earth Science Informatics, doi 10.1007/s12145-015-0219-1.

Ramani, S.E., Pitchaimani, K., & Gnanamanickam, V.R. (2011). GIS based landslide susceptibility mapping of Tevankarai Ar sub-watershed, Kodaikkanal, India using binary logistic regression analysis, Journal of Mountain Science, 8(4), 505–517.

Ramnarine, R., Harris, W.G., & Grunwald, S. (2015). Predicting the Distribution of Naturally Occurring Phosphatic Soils across a Countywide Landscape, Florida, USA, Communications in Soil Science and Plant Analysis, 46(11), 1391–1410.

Razandi, Y., Pourghasemi, H.R., Neisani, N.S., & Rahmati, O. (in press). Application of analytical hierarchy process, frequency ratio, and certainty factor models for groundwater potential mapping using GIS, Earth Science Informatics, doi: 10.1007/s12145-015-0220-8.

Refice, A., & Capolongo, D. (2002). Probabilistic modeling of uncertainties in earthquake-induced landslide hazard assessment, Computers and Geosciences, 28(6), 735–749.

Regmi, A.D., Yoshida, K., Pourghasemi, H.R., DhitaL, M.R., & Pradhan, B. (2014). Landslide susceptibility mapping along Bhalubang — Shiwapur area of mid-Western Nepal using frequency ratio and conditional probability models, Journal of Mountain Science, 11(5), 1266–1285.
Remondo, J., González-Díez, A., De Terán, J., & Cendrero, A. (2003). Landslide susceptibility models utilising spatial data analysis techniques. A case study from the lower Deba Valley, Guipuzcoa (Spain), Natural Hazards, 30(3), 267–279.
Reshmidevi, T.V., Eldho, T.I., & Jana, R. (2009). A GIS-integrated fuzzy rule-based inference system for land suitability evaluation in agricultural watersheds, Agricultural Systems, 101(1–2), 101–109.
Robinson Jr., G.R., Kapo, K.E., & Raines, G.L. (2004). A GIS Analysis to Evaluate Areas Suitable for Crushed Stone Aggregate Quarries in New England, USA, Natural Resources Research, 13(3), 143–159.
Romanelli, A., Lima, M.L., Londoño, O.M.Q., Martínez, D.E., & Massone, H.E. (2012). A Gis-Based Assessment of Groundwater Suitability for Irrigation Purposes in Flat Areas of the Wet Pampa Plain, Argentina, Environmental Management, 50(3), 490–503.
Romero-Calcerrada, R., Novillo, C.J., Millington, J.D.A., & Gomez-Jimenez, I. (2008). GIS analysis of spatial patterns of human-caused wildfire ignition risk in the SW of Madrid (Central Spain), Landscape Ecology, 23(3), 341–354.
Rüger, N., Schlüter, M., & Matthies, M. (2005). A fuzzy habitat suitability index for populus euphratica in the Northern Amudarya delta (Uzbekistan), Ecological Modelling, 184(2–4), 313–328.
Sadeghi, B., & Khalajmasoumi, M. (2015). A futuristic review for evaluation of geothermal potentials using fuzzy logic and binary index overlay in GIS environment, Renewable and Sustainable Energy Reviews, 43, 818–831.
Saeidi, V., Pradhan, B., Idrees, M.O., & Abd Latif, Z. (2014). Fusion of airborne LiDAR with multispectral SPOT 5 image for enhancement of feature extraction using Dempster–Shafer theory, IEEE Transctions on Geoscience and Remote Sensing, 52(10), 6017–6025.
Sahoo, S., Jha, M., Kumar, N., & Chowdary, V. (2015). Evaluation of GIS-based multicriteria decision analysis and probabilistic modeling for exploring groundwater prospects, Environmental Earth Sciences, 74(3), 2223–2246.
Sakamoto, A. & Fukui, H. (2004). Development and application of a livable environment evaluation support system using Web GIS, Journal of Geographical Systems, 6(2), 175–195.
Samranpong, C., Ekasingh, B., & Ekasingh, M. (2009). Economic land evaluation for agricultural resource management in Northern Thailand, Environmental Modelling and Software, 24(12), 1381–1390.
Schindler, D., Grebhan, K., Albrecht, A., Schönborn, J., & Kohnle, U. (2012). GIS-based estimation of the winter storm damage probability in forests: a case study from Baden-Wuerttemberg (Southwest Germany), International Journal of Biometeorology, 56(1), 57–69.
Schmidt, J., & Hewitt, A. (2004). Fuzzy land element classification from DTMs based on geometry and terrain position, Geoderma, 121(3–4), 243–256.
Schotten, K., Goetgeluk, R., Hilferink, M., Rietveld, P., & Scholten, H. (2001). Residential Construction, Land Use and the Environment. Simulations for the Netherlands Using a GIS-Based Land Use Model, Environmental Modeling and Assessment, 6(2), 133–143.
Semple, H., Cudnik, M., Sayre, M., Keseg, D., Warden, C., & Sasson, C. (2013). Identification of High-Risk Communities for Unattended Out-of-Hospital Cardiac Arrests Using GIS, Journal of Community Health, 38(2), 277–284.
Şener, E. & Şener, S. (2015). Evaluation of groundwater vulnerability to pollution using fuzzy analytic hierarchy process method, Environmental Earth Sciences, 73(12), 8405–8424.
Shad, R., Saadi Mesgari, M., Abkar, A., & Shad, A. (2009). Predicting air pollution using fuzzy genetic linear membership kriging in GIS, Computers, Environment and Urban Systems, 33(6), 472–481.
Shadman Roodposhti, M., Rahimi, S., & Jafar Beglou, M. (2014). PROMETHEE II and fuzzy AHP: an enhanced GIS-based landslide susceptibility mapping, Natural Hazards, 73(1), 77–95.
Shahabi, H., Hashim, M. & Bin Ahmad, B. (2015). Remote sensing and GIS-based landslide susceptibility mapping using frequency ratio, logistic regression, and fuzzy logic methods at the central Zab basin, Iran, Environmental Earth Sciences, 73(12), 8647–8668.
Shahid, S., Nath, S.K., & Kamal, A.S.M.M. (2002). GIS Integration of Remote Sensing and Topographic Data Using fuzzy Logic for Ground Water Assessment in Midnapur District, India, Geocarto International, 17(3), 69–74.
Sharma, L.P., Patel, N., Ghose, M.K., & Debnath, P. (2013). Synergistic application of fuzzy logic and geo-informatics for landslide vulnerability zonation—a case study in Sikkim Himalayas, India, Applied Geomatics, 5(4), 271–284.
Sheng, J., Wan, L.H., Lv, H., & Wen, Z.H. (2012). Lahar risk-division of Changbai Moutian region, China, Applied Mechanics and Materials, 166(1), 2601–2604.
Shengyuan, Z., Qiuming, C., & Zhijun, C. (2008). Omnibus weights of evidence method implemented in GeoDAS GIS for information extraction and integration, Journal of China University of Geosciences, 19(4), 404–409.
Shi, H., Gao, Q., Qi, Y., Liu, J. & Hu, Y. (2009). Wind erosion hazard assessment of the Mongolian Plateau using FCM and GIS techniques, Environmental Earth Sciences, 61(4), 689–697.
Shi, J.S., Ma, R., Liu, J.C., & Zhang, Y.L. (2013). Suitability assessment of deep groundwater for drinking, irrigation and industrial purposes in Jiaozuo City, Henan Province, north China, Chinese Sciences Bulletin, 58(25), 3098–3110.
Shi, Y., Li, F., Fan, M., Liu, H., & Yang, X. (2014). Applications of Variable fuzzy Set Theory and GIS for Water Resources Vulnerability Assessment of Yellow River Delta, Applied Mechanics and Materials, 700, 501–505.

Shirzadi, A., Saro, L., Joo, O.H., & Chapi, K. (2012). A GIS-based logistic regression model in rock-fall susceptibility mapping along a mountainous road: Salavat Abad case study, Kurdistan, Iran, Natural Hazards, 64(2), 1639–1656.
Sicat, R.S., Carranza, E.J.M., & Nidumolu, U.B. (2005). Fuzzy modeling of farmers' knowledge for land suitability classification, Agricultural Systems, 81(3), 49–75.
Simav, O., Seker, D.Z., & Gazioglu, C. (2013). Coastal inundation due to sea level rise and extreme sea state and its potential impacts: Çukurova Delta case, Turkish Journal of Earth Sciences, 22(4), 671–680.
Široký, P., Kubelová, M., Bedná, M., Modrý, D., Hubálek, Z., & Tkadlec, E. (2011). The distribution and spreading pattern of Dermacentor reticulatus over its threshold area in the Czech Republic—How much is range of this vector expanding?, Veterinary Parasitology, 183(1–2), 130–135.
Skov, F., & Svenning, J.-C. (2003). Predicting plant species richness in a managed forest, Forest Ecology and Management, 180(1–3), 583–593.
Solaimani, K., Mousavi, S.Z., & Kavian, A. (2013). Landslide susceptibility mapping based on frequency ratio and logistic regression models, Arabian Journal of Geosciences, 6(7), 2557–2569.
Soltani, S.R., Mahiny, A.S., Monavari, S.M., & Alesheikh, A.A. (2013). Sustainability through uncertainty management in urban land suitability assessment, Environmental Engineering Science, 30(4), 170–178.
Soto, M.E.C. (2012). The identification and assessment of areas at risk of forest fire using fuzzy methodology, Applied Geography, 35(1–2), 199–207.
Steinhardt, U. (1998). Applying the fuzzy set theory for medium and small scale landscape assessment, Landscape and Urban Planning, 41(3–4), 203–208.
Stoms, D.M., McDonald, J.M. & Davis, F.W. (2002). Fuzzy assessment of land suitability for scientific research reserves, Environmental Management, 29(4), 545–558.
Subburayalu, S.K., Jenhani, I., & Slater, B.K. (2014). Disaggregation of component soil series on an Ohio County soil survey map using possibilistic decision trees, Geoderma, 213, 334–345.
Sujatha, E.R., & Rajamanickam, V. (2011). Landslide susceptibility mapping of Tevankarai Ar sub-watershed, Kodaikkanal taluk, India, using weighted similar choice fuzzy model, Natural Hazards, 59(1), 401–425.
Sun, Z., Zhang, J., Zhang, Q., Hu, Y., Yan, D., & Wang, C. (2014). Integrated risk zoning of drought and waterlogging disasters based on fuzzy comprehensive evaluation in Anhui Province, China, Natural Hazards, 71(3), 1639–1657.
Sutcu, E.C. (2012). Use of GIS to discover potential coalfields in Yatagan–Milas area in Turkey, International Journal of Coal Geology, 98, 95–109.
Svoray, T., Gancharski, S.B., Henkin, Z., & Gutman, M. (2004). Assessment of herbaceous plant habitats in water-constrained environments: predicting indirect effects with fuzzy logic, Ecological Modelling, 180(4), 537–556.
Taboada, J., Rivas, T., Saavedra, A., Ordóñez, C., Bastante, F., & Giráldez, E. (2008). Evaluation of the reserve of a granite deposit by fuzzy kriging, Engineering Geology, 99(1–2), 23–30.
Talaei, R. (2014). Landslide susceptibility zonation mapping using logistic regression and its validation in Hashtchin Region, northwest of Iran, Journal of the Geological Society of India, 84(1), 68–86.
Tang, C., & Zhu, J. (2006). Torrent risk zonation in the Upstream Red River Basin based on GIS, Journal of Geographical Sciences, 16(4), 479–486.
Tang, J., Chen, F., & Schwartz, S.S. (2012). Assessing spatiotemporal variations of greenness in the Baltimore–Washington corridor area, Landscape and Urban Planning, 105(3), 296–306.
Tang, F.H., Zhang, S.M., Yang, S.L., & Cui, X.S. (2013). Predicting System of Flying Squid in North Pacific Based on the Bayesian Theory, Applied Mechanics and Materials, 336(1), 1968–1973.
Tangestani, M.H., & Moore, F. (2002). The use of Dempster–Shafer model and GIS in integration of geoscientific data for porphyry copper potential mapping, north of Shahr-e-Babak, Iran, International Journal of Applied Earth Observation and Geoinformation, 4(1), 65–74.
Tangestani, M.H., & Moore, F. (2003). Mapping porphyry copper potential with a fuzzy model, northern Shahr-e-Babak, Iran, Australian Journal of Earth Sciences, 50(3), 311–317.
Tangestani, M. (2009). A comparative study of Dempster–Shafer and fuzzy models for landslide susceptibility mapping using a GIS: An experience from Zagros Mountains, SW Iran, Journal of Asian Earth Sciences, 35(1), 66–73.
Thiam, A.K. (2005). An evidential reasoning approach to land degradation evaluation: Dempster–Shafer theory of evidence, Transactions in GIS, 9(4), 507–520.
Tripathi, R., Nayak, A.K., Shahid, M., Lal, B., Gautam, P., Raja, R., Mohanty, S., Kumar, A., Panda, B.B., & Sahoo, R.N. (2015). Delineation of soil management zones for a rice cultivated area in eastern India using fuzzy clustering, CATENA, 133, 128–136.
Tsutsumida, N., Saizen, I., Matsuoka, M., & Ishii, R. (2015). Addressing urban expansion using feature-oriented spatial data in a peripheral area of Ulaanbaatar, Mongolia, Habitat International, 47, 196–204.
Tucker, K., Rushton, S.P., Sanderson, R.A., Martin, E.B., & Blaiklock, J. (1997). Modelling bird distributions — a combined GIS and bayesian rule-based approach, Landscape Ecology, 12(2), 77–93.
Uddameri, V., & Honnungar, V. (2007). Combining rough sets and GIS techniques to assess aquifer vulnerability characteristics in the semi-arid South Texas, Environmental Geology, 51(6), 931–939.
Urbański, J.A., & Szymelfenig, M. (2003). GIS-based mapping of benthic habitats, Estuarine, Coastal and Shelf Science, 56 (1), 99–109.

Vadrevu, K., Eaturu, A., & Badarinath, K. (2010). Fire risk evaluation using multicriteria analysis-a case study, Environmental Monitoring and Assessment, 166(1–4), 223–239.
Vafai, F., Hadipour, V., & Hadipour, A. (2013). Determination of shoreline sensitivity to oil spills by use of GIS and fuzzy model. Case study – The coastal areas of Caspian Sea in north of Iran, Ocean and Coastal Management, 71, 123–130.
Vahidnia, M.H., Alesheikh, A.A., & Alimohammadi, A. (2009). Hospital site selection using fuzzy AHP and its derivatives, Journal of Environmental Management, 90(1), 3048–3056.
Vakalis, D., Sarimveis, H., Kiranoudis, C.T., Alexandridis, A., & Bafas, G. (2004). A GIS based operational system for wildland fire crisis management II. System architecture and case studies, Applied Mathematical Modelling, 28(4), 411–425.
Venkataraman, G., Babu Madhavan, B., Ratha, D.S., Antony, J.P., Goyal, R.S., & Sinha Roy, S. (2000). Spatial modeling for base-metal mineral exploration through integration of geological data sets, Natural Resources Research, 9(1), 27–42.
Venkatramanan, S., Chung, S.Y., Rajesh, R., Lee, S.Y., Ramkumar, T., & Prasanna, M.V. (in press). Comprehensive studies of hydrogeochemical processes and quality status of groundwater with tools of cluster, grouping analysis, and fuzzy set method using GIS platform: a case study of Dalcheon in Ulsan City, Korea, Environmental Science and Pollution Research, doi: 10.1007/s11356-015-4290-4.
Verbeeck, K., Van Orshoven, J., & Hermy, M. (2011). Measuring extent, location and change of imperviousness in urban domestic gardens in collective housing projects, Landscape and Urban Planning, 100(1–2), 57–66.
Vijith, H., & Madhu, G. (2008). Estimating potential landslide sites of an upland sub-watershed in Western Ghat's of Kerala (India) through frequency ratio and GIS, Environmental Geology, 55(7), 1397–1405.
Vijith, H., Suma, M., Rekha, V.B., Shiju, C., & Rejith, P.G. (2012). An assessment of soil erosion probability and erosion rate in a tropical mountainous watershed using remote sensing and GIS, Arabian Journal of Geosciences, 5(4), 797–805.
Wan, S., Lei, T.C., Huang, P.C., Chou, & T.Y. (2008). The knowledge rules of debris flow event: A case study for investigation Chen Yu Lan River, Taiwan, Engineering Geology, 98, 102–114.
Wan, S., Lei, T.C., & Chou, T.Y. (2010). A novel data mining technique of analysis and classification for landslide problems, Natural Hazards, 52(1), 211–230.
Wan, S., Lei, T.C., & Chou, T.Y. (2012). A landslide expert system: image classification through integration of data mining approaches for multi-category analysis, International Journal of Geographical Information Science, 26(4), 747–770.
Wang, W.D., Xie, C.-M., & Du, X.-G. (2009). Landslides susceptibility mapping in Guizhou province based on fuzzy theory, Mining Science and Technology, 19(3), 399–404.
Wang, H.J., He, S.W., Liu, X.J., Dai, L., Pan, P., Hong, S., & Zhang, W.T. (2013). Simulating urban expansion using a cloud-based cellular automata model: A case study of Jiangxia, Wuhan, China, Landscape and Urban Planning, 110, 99–112.
Wang, B., Wang, X., & Chen, Z. (2013). A hybrid framework for reservoir characterization using fuzzy ranking and an artificial neural network, Computers and Geosciences, 57, 1–10.
Weissteiner, C.J., Boschetti, M., Böttcher, K., Carrara, P., Bordogna, G., &Brivio, P.A. (2011). Spatial explicit assessment of rural land abandonment in the Mediterranean area, Global and Planetary Change, 79(1), 20–36.
Wikramanayake, E., McKnight, M., Dinerstein, E., Joshi, A., Gurung, B., & Smith, D. (2004). Designing a conservation landscape for tigers in human-dominated environments, Conservation Biology, 18(3), 839–844.
Wiley, D.N., Thompson, M., Pace, R.M., & Levenson, J. (2011). Modeling speed restrictions to mitigate lethal collisions between ships and whales in the Stellwagen Bank National Marine Sanctuary, USA, Biological Conservation, 144(9), 2377–2381.
Wood, L.J., & Dragicevic, S. (2007). GIS-based multicriteria evaluation and fuzzy sets to identify priority sites for marine protection, Biodiversity and Conservation, 16(9), 2539–2558.
Wu, F. (1998). Simulating urban encroachment on rural land with fuzzy-logic-controlled cellular automata in a geographical information system, Journal of Environmental Management, 53(4), 293–308.
Wu, Y., Huang, J., Yuan, Y., Cui, W., & Zhan, Y. (2012). Simulation of Land Use/Cover Change for Wuhan City Based on GIS and CA, Journal of Convergence Information Technology, 7(1), 253–260.
Wu, X., Niu, R., Ren, F. & Peng, L. (2013). Landslide susceptibility mapping using rough sets and back-propagation neural networks in the Three Gorges, China, Environmental Earth Sciences, 70(3), 1307–1318.
Xia, R., & Chen, Z. (2015). Integrated water-quality assessment of the Huai river basin in China, Journal of Hydrologic Engineering, 20(2), p-1, 1p.
Xie, M., Esaki, T., & Zhou, G. (2004). GIS-Based Probabilistic Mapping of Landslide Hazard Using a Three-Dimensional Deterministic Model, Natural Hazards, 33(2), 265–282.
Xu, Z.-W. (2001). GIS and ANN model for landslide susceptibility mapping, Journal of Geographical Sciences, 11(3), 374–381.
Yalcin, A., Reis, S., Aydinoglu, A.C., & Yomralioglu, T. (2011). A GIS-based comparative study of frequency ratio, analytical hierarchy process, bivariate statistics and logistics regression methods for landslide susceptibility mapping in Trabzon, NE Turkey, CATENA, 85(3), 274–287.
Yang, Y.-J., & Yang, J.-S. (2005). Potential soil salinization using Dempster–Shafer evidence theory, Transactions of the Chinese Society of Agricultural Engineering, 21(4), 30–33.
Yang, Y.-J., Yang, J.-S., Liu, G.-M., & Yang, X.-Y. (2005). Space-time variability and prognosis of soil salinization in Yucheng City, China, Pedosphere, 15(6), 797–804.
Yang, F., Zeng, G., Du, C., Tang, L., Zhou, J., & Li, Z. (2008). Spatial analyzing system for urban land-use management based on GIS and multi-criteria assessment modeling, Progress in Natural Science, 18(10), 1279–1284.

Yang, M.-Y., Van Coillie, F., Hens, L., De Wulf, R., Ou, X.-K. & Zhang, Z.-M. (2014a). Nature conservation versus scenic quality: A GIS approach towards optimized tourist tracks in a protected area of Northwest Yunnan, China, Journal of Mountain Science, 11(1), 142–155.
Yang, Q., Xie, Y., Li, W., Jiang, Z., Li, H., & Qin, X. (2014b). Assessing soil erosion risk in karst area using fuzzy modeling and method of the analytical hierarchy process, Environmental Earth Sciences, 71(1), 287–292.
Yi, C.-S., Lee, J.-H., & Shim, M.-P. (2010). GIS-based distributed technique for assessing economic loss from flood damage: pre-feasibility study for the Anyang Stream Basin in Korea, Natural Hazards, 55(2), 251–272.
Yigit, O. (2012). Discovered and undiscovered gold endowment of Turkey: a quantitative mineral resource assessment using GIS and rank statistical analysis, Mineralium Deposita, 47(5), 521–534.
Yilmaz, I., Marschalko, M., & Bednarik, M. (2013). An assessment on the use of bivariate, multivariate and soft computing techniques for collapse susceptibility in GIS environ, Journal of Earth System Science, 122(2), 371–388.
Youssef, A.M., Pourghasemi, H.R., El-Haddad, B.A., & B.K. Dhahry (in press). Landslide susceptibility maps using different probabilistic and bivariate statistical models and comparison of their performance at Wadi Itwad Basin, Asir Region, Saudi Arabia, Bulletin of Engineering Geology and the Environment, doi 10.1007/s10064-015-0734-9.
Youssef, A.M., Pradhan, B., Pourghasemi, H.R., & Abdullahi, S. (in press). Landslide susceptibility assessment at Wadi Jawrah Basin, Jizan region, Saudi Arabia using two bivariate models in GIS, Geosciences Journal, doi 10.1007/s12303-014-0065-z.
Zahiri, H., Palamara, D.R., Flentje, P., Brassington, G.M., & Baafi, E. (2006). A GIS-based Weights-of-Evidence model for mapping cliff instabilities associated with mine subsidence, Environmental Geology, 51(3), 377–386.
Zamorano, M., Molero, E., Hurtado, A., Grindlay, A., & Ramos, A. (2008). Evaluation of a municipal landfill site in Southern Spain with GIS-aided methodology, Journal of Hazardous Materials, 160(2–3), 473–481.
Zeller, K.A., Nijhawan, S., Salom-Pérez, R., Potosme, S.H., & Hines, J.E. (2011). Integrating occupancy modeling and interview data for corridor identification: A case study for jaguars in Nicaragua, Biological Conservation, 144(2), 892–901.
Zeng, T.Q., & Zhou, Q. (2001). Optimal spatial decision making using GIS: a prototype of a real estate geographical information system (REGIS), International Journal of Geographical Information Science, 15(4), 307–321.
Zhang, L., & Guilbert, E. (2013). Automatic drainage pattern recognition in river networks, International Journal of Geographical Information Science, 27(12), 2319–2342.
Zhang, B., Zhang, Y., Chen, D., White, R.E., & Li, Y. (2004). A quantitative evaluation system of soil productivity for intensive agriculture in China, Geoderma, 123(3–4), 319–331.
Zhang, J., Wei, J., & Chen, Q. (2009). Mapping the farming-pastoral ecotones in China, Journal of Mountain Science, 6(1), 78–87.
Zhang, Z.X., Zhang, H.Y., & Zhou, D.W. (2010). Using GIS spatial analysis and logistic regression to predict the probabilities of human-caused grassland fires, Journal of Arid Environments, 74(3), 386–393.
Zhang, X., Fang, C., Wang, Z., & Ma, H. (2013a). Urban construction land suitability evaluation based on improved multi-criteria evaluation based on GIS (MCE-GIS): Case of New Hefei City, China, Chinese Geographical Science, 23(6), 740–753.
Zhang, Z., Sherman, R., Yang, Z., Wu, R., Wang, W., Yin, M., Yang, G., & Ou, X. (2013b). Integrating a participatory process with a GIS-based multi-criteria decision analysis for protected area zoning in China, Journal for Nature Conservation, 21 (4), 225–240.
Zhang, Z., Demšar, U., Rantala, J., & Virrantaus, K. (2014). A fuzzy multiple-attribute decision-making modelling for vulnerability analysis on the basis of population information for disaster management, International Journal of Geographical Information Science, 28(9), 1922–1939.
Zhang, J, Su, Y., Wu, J., & Liang, H. (2015). GIS based land suitability assessment for tobacco production using AHP and fuzzy set in Shandong province of China, Computers and Electronics in Agriculture, 114, 202–211.
Zhijun, T., Jiquan, Z., & Xingpeng, L. (2009). GIS-based risk assessment of grassland fire disaster in western Jilin province, China, Stochastic Environmental Research and Risk Assessment, 23(4), 463–471.
Zhou, Q., Charnpratheep, K., & Garner, B. (1997). Preliminary landfill site screening using fuzzy geographical information systems, Waste Management and Research, 15(2), p197.
Zhou, G., Esaki, T., Mitani, Y., Xie, M., & Mori, J. (2003). Spatial probabilistic modeling of slope failure using an integrated GIS Monte Carlo simulation approach, Engineering Geology, 68(3–4), 373–386.
Zhu, A.X., & Mackay, D.S. (2001). Effects of spatial detail of soil information on watershed modeling, Journal of Hydrology, 248(1–4), 54–77.
Zhu, A.-X., Band, L.E., Dutton, B., & Nimlos, T.J. (1996). Automated soil inference under fuzzy logic, Ecological Modelling, 90 (2), 123–145.
Zhu, Q.-W., Su, L., & Xie, H.-Q. (2006). Combining GIS with RS based on rough set mining method, Journal of Liaoning Technical University, 25(1), 28–31.
Zhu, A.-X., Wang, R., Qiao, J., Qin, C.-Z., Chen, Y., Liu, J., Du, F., Lin, Y., & Zhu, T. (2014). An expert knowledge-based approach to landslide susceptibility mapping using GIS and fuzzy logic, Geomorphology, 214, 128–138.
Zou, Q., Zhou, J., Zhou, C., Song, L., & Guo, J. (2013). Comprehensive flood risk assessment based on set pair analysis-variable fuzzy sets model and fuzzy AHP, Stochastic Environmental Research and Risk Assessment, 27(2), 525–546.

Appendix B. Methods, applications, and location for GIS papers with uncertain spatial data

Text reference	Method	Application	Location
Abbaspour et al. (2011)	Fuzzy AHP	Land suitability modeling	Iran
Abd Manap et al. (2014)	Frequency ratio	Groundwater resource modeling	Malaysia
Abdalla et al. (2014)	Fuzzy membership	Natural hazard modeling	Canada
Abdul Rahaman et al. (2015)	Fuzzy AHP	Groundwater resource modeling	India
Abdullahi & Pradhan (in press)	General probability theory	Land use modeling	Malaysia
Adab et al. (2013)	General probability theory	Natural hazard modeling	Iran
Ahadnejad et al. (2009)	General probability theory	Land use modeling	Iran
Ahilan et al. (2012)	General probability theory	Natural hazard modeling	Ireland
Akgün & Bulut (2007)	General probability theory	Landslide susceptibility modeling	Turkey
Akgün & Türk (2011)	Fuzzy membership	Natural hazard modeling	Turkey
Akgun et al. (2012)	General probability theory	Landslide susceptibility modeling	Turkey
Akgün et al. (2012)	Mamdani's fuzzy inference modeling	Landslide susceptibility modeling	Turkey
Akumu et al. (2015)	Fuzzy membership	Soil suitability modeling	Canada
Al-Abadi (2015)	General probability theory	Groundwater resource modeling	Iraq
Al-Ahmadi et al. (2009)	Fuzzy rules	Urban planning and modeling	Saudi Arabia
Al-Ahmadi et al. (2014)	General probability theory	Natural hazard modeling	Red Sea
Alesheikh et al. (2008)	Fuzzy membership	Natural hazard modeling	Iran
Alexakis & Sarris (2014)	Fuzzy membership	Land suitability modeling	Greece
Alexakis et al. (2014)	General probability theory	Landslide susceptibility modeling	Cyprus
Al-garni (1995)	General probability theory	Urban planning and modeling	Saudi Arabia
Aliniai et al. (in press)	FUZZY ordered weighted average	Land suitability modeling	Iran
Allen et al. (2007)	Fuzzy membership	Groundwater resource modeling	Canada
Al-Rafadain (2013)	General probability theory	Rain water harvesting modeling	Iraq
Al-sharif & Pradhan (2014)	Transition probability	Land use modeling	Libya
Althuwaynee et al. (2012)	Dempster–Shafer	Landslide susceptibility modeling	Malaysia
Althuwaynee et al. (2014)	Dempster–Shafer	Landslide susceptibility modeling	Korea
Amici et al. (2010)	Fuzzy classification	Habitat suitability modeling	Italy
Anane et al. (2012)	Fuzzy AHP	Land suitability modeling	Tunisia
Anbalagan et al. (in press)	Fuzzy membership	Landslide susceptibility modeling	India
Antonakos et al. (2014)	Fuzzy multi-criteria analysis	Groundwater resource modeling	Greece
Ardeshir et al. (2014)	Fuzzy AHP	Bridge location modeling	Iran
Arnous et al. (2011)	General probability theory	Landslide susceptibility modeling	Egypt
Assimakopoulos et al. (2003)	Fuzzy membership	Soil suitability modeling	Greece
Ayala-Carcedo et al. (2003)	Probability map	Rock-fall susceptibility modeling	Spain
Ayalew et al. (2011)	General probability theory	Landslide susceptibility modeling	Japan
Aydi et al. (2013)	Fuzzy AHP	Land suitability modeling	Tunisia
Aydin et al. (2010)	Fuzzy multi-criteria analysis	Land suitability modeling	Turkey
Baalousha (2010)	Probability map	Underground vulnerability modeling	Palestine

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Text reference	Method	Application	Location
Badia et al. (2011)	General probability theory	Wilderness land modeling	Mediterranean
Bai et al. (2011)	Probability map	Landslide susceptibility modeling	China
Baja et al. (2002)	Fuzzy membership	Land suitability modeling	Australia
Baja et al. (2007)	Fuzzy multi-criteria analysis	Land use modeling	Australia
Balla et al. (2013)	Fuzzy membership	Geo-historical modeling	Greece
Batty et al. (1999)	General probability theory	Urban planning and modeling	Not available
Bekkby et al. (2008)	Probability map	Marine environmental modeling	Norway
Benomar et al. (2009)	General probability theory	Mineral resources modeling	China
Beucher et al. (2014)	Fuzzy membership	Soil suitability modeling	Finland
Biass & Bonadonna (2013)	Bayesian probability	Natural hazard modeling	Ecuador
Biass et al. (2012)	Probability map	Natural hazard modeling	Ecuador
Biass et al. (2013)	Probability map	Natural hazard modeling	Ecuador
Binaghi et al. (1998)	Dempster–Shafer	Landslide susceptibility modeling	Italy
Biswas (2009)	Transition probability	Groundwater resource modeling	India
Bojórquez-Tapia et al. (2013)	Fuzzy membership	Land degradation modeling	Mexico
Bone et al. (2005)	Fuzzy membership	Natural hazard modeling	Canada
Bone et al. (2006)	Fuzzy membership	Insect infestation modeling	Not available
Bone et al. (2007)	Fuzzy membership	Forest management modeling	Canada
Boroushaki and Malczewski (2010)	Fuzzy majority procedure	Land suitability modeling	Not available
Brown et al. (2003)	Fuzzy membership	Mineral potential modeling	Australia
Bruce et al. (2014)	General probability theory	Whale migration modeling	Australia
Bui et al. (2012a)	Adaptive neuro-fuzzy inference system (ANFIS)	Landslide susceptibility modeling	Vietnam
Bui et al. (2012b)	Fuzzy membership	Landslide susceptibility modeling	Vietnam
Burrough et al. (2001)	Fuzzy *k*-means	Forest management modeling	USA
Busch (2012)	Fuzzy rules	Environmental modeling	Germany
Canning (2005)	Dempster–Shafer	Archaeological predictive modeling	Australia
Cao et al. (2015)	Rough set	Urban planning and modeling	China
Capolongo et al. (2002)	General probability theory	Landslide susceptibility modeling	Italy
Carranza et al. (2005)	Dempster–Shafer	Mineral potential modeling	Zambia
Carrasco et al. (2003)	Probability map	Landslide susceptibility modeling	Spain
Carver et al. (2012)	Fuzzy multi-criteria analysis	Wilderness land modeling	Scotland
Cassel-Gintz, & Petschel-Held (2000)	Fuzzy membership	Environmental modeling	Germany
Ceballos-Silva & López-Blanco (2003)	Fuzzy multi-criteria analysis	Land use modeling	Mexico
Chacón et al. (2006)	Dempster–Shafer	Landslide susceptibility modeling	Spain
Chang & Shiuan (in press)	Rough set	Landslide susceptibility modeling	Taiwan
Chang et al. (2008)	Fuzzy multi-criteria analysis	Land suitability modeling	USA

Appendix B (*continued*)

Text reference	Method	Application	Location
Chang et al. (2009)	Fuzzy AHP	Land suitability modeling	Taiwan
Charabi & Gastli (2011)	Fuzzy multi-criteria analysis	Site suitability modeling	Oman
Charnpratheep et al. (1997)	Fuzzy AHP	Land suitability modeling	Thailand
Chen et al. (2005)	Probability map	Mineral resources modeling	China
Chen et al. (2015)	General probability theory	Landslide susceptibility modeling	China
Cheng et al. (2011)	Fuzzy membership	Mineral potential modeling	China
Choi et al. (2010)	Fuzzy membership	Mineral potential modeling	Korea
Choi et al. (2011a)	General probability theory	Marine environmental modeling	Korea
Choi et al. (2011b)	General probability theory	Urban planning and modeling	Korea
Chubey & Hathout (2004)	Transition probability	Natural hazard modeling	Canada
Coelho et al. (2012)	Fuzzy multi-criteria analysis	Water resource management	Brazil
Cowell & Zeng (2003)	Fuzzy membership	Marine environmental modeling	Australia
Crider et al. (2014)	General probability theory	Health risk modeling	USA
Dahal et al. (2014)	General probability theory	Landslide susceptibility modeling	Nepal
Daniel & Lauffenburger (2012)	Dempster–Shafer	Speed limit modeling	Not available
Dasgupta et al. (2013)	Fuzzy membership	Land use modeling	India
Davidson et al. (1994)	Fuzzy membership	Land suitability modeling	Greece
Davis & Keller (1997)	Fuzzy membership	Land suitability modeling	Canada
De Runz et al. (2014)	Fuzzy membership	Geo-historical modeling	France
Di Martino & Sessa (2011)	Fuzzy C-means	Hotspot modeling	USA
Diodato & Ceccarelli (2004)	Probability map	Soil suitability modeling	Italy
Diodato & Ceccarelli (2006)	Probability map	Groundwater resource modeling	Italy
Dixon (2005a)	Neuro fuzzy	Groundwater resource modeling	USA
Dixon (2005b)	Fuzzy rules	Groundwater resource modeling	USA
Djamaluddin et al. (2011)	Fuzzy membership	Land movement modeling	China
Dlamini (2011)	Bayesian probability	Natural hazard modeling	Swaziland
Donevska et al. (2012)	Fuzzy AHP	Land suitability modeling	Macedonia
Donglin et al. (2012)	Bayesian probability	Mineral potential modeling	China
Dragićević et al. (2015)	Fuzzy multi-criteria analysis	Landslide susceptibility modeling	Canada
Du et al. (2012)	Rough set	Land suitability modeling	China
Edwards et al. (2015)	General probability theory	Recreational modeling	Australia
Eikaas et al. (2005)	General probability theory	Fish habitat modeling	New Zealand
El-Haddad (in press)	Dempster–Shafer	Landslide susceptibility modeling	Saudi Arabia
Elheishy et al. (2013)	Rough set	Shelter suitability modeling	Egypt
Eskandari & Emilio Chuvieco (2015)	General probability theory	Fire propagation modeling	Iran
Feizizadeh & Blaschke (2013)	Dempster–Shafer	Landslide susceptibility modeling	Iran
Feizizadeh & Blaschke (2014)	Dempster–Shafer	Landslide susceptibility modeling	Iran
Feizizadeh et al. (2013)	Fuzzy AHP	Landslide susceptibility modeling	Iran
Feizizadeh et al. (2014a)	Dempster–Shafer	Landslide susceptibility modeling	Iran

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Text reference	Method	Application	Location
Feizizadeh et al. (2014b)	Dempster–Shafer	Landslide susceptibility modeling	Iran
Feizizadeh et al. (2014c)	Fuzzy AHP	Landslide susceptibility modeling	Iran
Feng et al. (2006)	General probability theory	Landslide susceptibility modeling	China
Feoli et al. (2002)	Fuzzy membership	Environmental modeling	Ethiopia
Feoli et al. (2009)	Fuzzy membership	Land suitability modeling	Ethiopia
Ferrier & Wadge (1997)	Dempster–Shafer	Sedimentary basins modeling	England
Filippini-Alba & de Souza Filho (2010)	Fuzzy membership	Environmental modeling	Brazil
Flantua et al. (2007)	General probability theory	Geo-historical modeling	Colombia
Fleming et al. (2007)	Fuzzy membership	Health risk modeling	Southern Africa
Foody & Boyd (1999)	Neuro fuzzy	Land suitability modeling	Ghana
Friedrich et al. (2002)	Fuzzy membership	Soil suitability modeling	Germany
Fustes et al. (2014)	Fuzzy classification	Marine environmental modeling	Spain
Gahegan & Flack (1999)	Dempster–Shafer	Land use modeling	Not available
Ge et al. (2011)	Rough set	Urban planning and modeling	China
Gemitzi et al. (2007)	Fuzzy AHP	Land suitability modeling	Greece
Ghayoumian et al. (2007)	Fuzzy membership	Groundwater resource modeling	Iran
Ghinoi & Chung (2005)	Fuzzy membership	Snowpack instability modeling	Italy
Ghosh & Carranza (2010)	Dempster–Shafer	Landslide susceptibility modeling	India
Gimpel et al. (2015)	Fuzzy membership	Marine environmental modeling	Germany
Giordano & Liersch (2012)	Fuzzy rules	Soil salinization modeling	Uzbekistan
Giuffrida et al. (2014)	Rough set	Land use modeling	Italy
Gong et al. (2011)	General probability theory	Health risk modeling	USA
González-Álvarez et al. (2010)	Fuzzy membership	Mineral potential modeling	Australia
Gorsevski & Jankowski (2010)	Fuzzy membership	Landslide susceptibility modeling	USA
Gorsevski et al. (2005)	Dempster–Shafer	Landslide susceptibility modeling	USA
Gorsevski et al. (2012)	Fuzzy multi-criteria analysis	Land suitability modeling	Macedonia
Gorsevski et al. (2013)	Fuzzy membership	Wind farm suitability modeling	USA
Grekousis et al. (2013)	Fuzzy classification	Urban planning and modeling	Greece
Guo et al. (2007)	Fuzzy membership	Air pollution modeling	USA
Guo et al. (2014)	Fuzzy membership	Natural hazard modeling	China
Guoxin et al. (2004)	General probability theory	Land use modeling	Worldwide
Gupta et al. (2008)	Neuro fuzzy	Landslide susceptibility modeling	India
Hajehforooshnia et al. (2011)	Fuzzy AHP	Wilderness land modeling	Iran
Hao et al. (2014)	Probability map	Biological hazard modeling	China
Harris et al. (2001)	Probability map	Mineral potential modeling	Canada
Hashemi et al. (2013)	General probability theory	Natural hazard modeling	Iran
He et al. (2007)	Bayesian probability	Geo-historical modeling	USA
He et al. (2010)	Probability map	Mineral potential modeling	China
Hennecke (2004)	General probability theory	Coastal modeling	Australia

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Text reference	Method	Application	Location
Houshyar et al. (2014)	Fuzzy AHP	Land suitability modeling	Iran
Hu et al. (2011)	Bayesian probability	Health risk modeling	China
Huang & Cai (2007)	Transition probability	Land use modeling	China
Huang et al. (2007)	General probability theory	Land use modeling	China
Huang et al. (2011)	Fuzzy classification	Marine environmental modeling	Australia
Ilanloo (2011)	Fuzzy membership	Landslide susceptibility modeling	Iran
Jalayer et al. (2014)	Bayesian probability	Natural hazard modeling	Africa
Jasiewicz (2011)	Mamdani's fuzzy inference modeling	Natural hazard modeling	USA
Jebur et al. (2015)	Dempster–Shafer	Natural hazard modeling	Malaysia
Jeong et al. (2013)	Fuzzy AHP	Land suitability modeling	Spain
Jiao et al. (2012)	Fuzzy membership	Land suitability modeling	China
Jie et al. (2012)	General probability theory	Natural hazard modeling	China
Joerin & Musy (2000)	Rough set	Land suitability modeling	Switzerland
Jordan et al. (2007)	General probability theory	Soil suitability modeling	Ireland
Jung & Merwade (2012)	Fuzzy membership	Natural hazard modeling	USA
Kalantari et al. (2014)	General probability theory	Natural hazard modeling	Sweden
Kanungo et al. (2006)	Neuro fuzzy	Landslide susceptibility modeling	India
Kanungo et al. (2009)	Fuzzy membership	Landslide susceptibility modeling	India
Kayastha (2012)	Fuzzy membership	Landslide susceptibility modeling	Nepal
Khamespanah et al. (2013)	Dempster–Shafer	Seismic vulnerability modeling	Iran
Khan et al. (2014)	Rough set	Groundwater resource modeling	India
Khoi & Murayama (2010)	Fuzzy AHP	Land suitability modeling	Vietnam
Kiavarz Moghaddam et al. (2014)	Fuzzy multi-criteria analysis	Geothermal modeling	Japan
Kim et al. (2006)	General probability theory	Ground subsidence modeling	Korea
Kirschbaum et al. (in press)	Fuzzy membership	Landslide susceptibility modeling	Central America and Caribbean Islands
Klingseisen et al. (2008)	Fuzzy membership	Land suitability modeling	Australia
Ko et al. (2006)	General probability theory	Marine environmental modeling	North-Eastern Pacific
Kocabas & Dragicevic (2013)	Bayesian probability	Land use modeling	Canada
Kollias & Kalivas (1998)	Fuzzy membership	Soil suitability modeling	Greece
Kollias et al. (1999)	Fuzzy membership	Soil suitability modeling	Greece
Kontoes et al. (1993)	Dempster–Shafer	Land use modeling	Not available
Kordi & Anders Brandt (2012)	Fuzzy AHP	Dam location modeling	Costa Rica
Kritikos & Davies (in press)	Fuzzy membership	Landslide susceptibility modeling	New Zealand
Kühmaier et al. (2014)	Fuzzy multi-criteria analysis	Energy wood terminal location modeling	Austria
Kumar & Anbalagan (2015)	Fuzzy membership	Landslide susceptibility modeling	India
Kundu et al. (2013)	General probability theory	Landslide susceptibility modeling	India
Lagacherie et al. (2000)	Possibility theory	Soil suitability modeling	France
Lai et al. (2015)	Fuzzy multi-criteria analysis	Natural hazard modeling	China
Lamelas et al. (2008)	Probability map	Landslide susceptibility modeling	Spain

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Text reference	Method	Application	Location
Lark & Bolam (1997)	Fuzzy membership	Soil suitability modeling	United Kingdom
Lee & Choi (2003)	General probability theory	Landslide susceptibility modeling	Korea
Lee (2004)	Bayesian probability	Landslide susceptibility modeling	Korea
Lee et al. (2002)	Bayesian probability	Landslide susceptibility modeling	Korea
Lee et al. (2013a)	Dempster–Shafer	Landslide susceptibility modeling	Korea
Lee et al. (2013b)	Bayesian probability	Urban planning and modeling	Taiwan
Lee et al. (2014)	Frequency ratio	Landslide susceptibility modeling	Korea
Lee et al. (2015)	Adaptive neuro-fuzzy inference system (ANFIS)	Landslide susceptibility modeling	Korea
Lei et al. (2008)	Rough set	Agricultural image classification	Taiwan
Leung et al. (2007)	Rough set	Land suitability modeling	Hong Kong
Lewis et al. (2014)	Fuzzy membership	Land suitability modeling	USA
Li et al. (2001)	General probability theory	Natural hazard modeling	China
Li et al. (2010)	General probability theory	Landslide susceptibility modeling	China
Li et al. (2011)	General probability theory	Mineral potential modeling	China
Li et al. (2012)	Fuzzy AHP	Landslide susceptibility modeling	China
Li et al. (2015)	Dempster–Shafer	Landslide susceptibility modeling	Iran
Likkason et al. (1997)	Dempster–Shafer	Geo-physical modeling	Nigeria
Lin & Lin (2013)	Fuzzy AHP	Urban planning and modeling	Taiwan
Lisitsin et al. (2014)	Fuzzy membership	Mineral potential modeling	Australia
Lister et al. (2014)	General probability theory	Land use modeling	USA
Liu & Phinn (2003)	Fuzzy membership	Urban planning and modeling	Australia
Liu (2012)	Fuzzy constrained method	Urban planning and modeling	Australia
Liu et al. (2009)	General probability theory	Vegetation coverage modeling	China
Liu et al. (2011)	General probability theory	Land use modeling	China
Liu et al. (2012)	Fuzzy AHP	Natural hazard modeling	China
Liu et al. (2013)	Rough set	Land suitability modeling	China
Liu et al. (2015)	Dempster–Shafer	Tungsten polymetallic mineralization modeling	China
Lorz et al. (2010)	General probability theory	Natural hazard modeling	South-Eastern European countries
Lu et al. (2012)	Fuzzy membership	Habitat suitability modeling	China
Lu et al. (2014)	Fuzzy risk modeling	Marine environmental modeling	China
Lucas et al. (2012)	Possibility theory	Disaster management modeling	Germany
Ludwig et al. (2003)	Fuzzy membership	Environmental modeling	Germany
Ma et al. (2006)	Fuzzy membership	Economic modeling	China
Magesh et al. (2015)	Fuzzy membership	Mineral potential modeling	India
Magliulo et al. (2008)	General probability theory	Landslide susceptibility modeling	Italy
Maina et al. (2008)	Fuzzy AHP	Marine environmental modeling	Western Indian Ocean
Malczewski & Rinner (2005)	Fuzzy multi-criteria analysis	Urban planning and modeling	Canada
Malczewski (2006)	Fuzzy membership	Land suitability modeling	Mexico

Appendix B (*continued*)

Text reference	Method	Application	Location
Malekmohammadi et al. (2012)	Fuzzy rules	Water quality modeling	Iran
Malinowska (2011)	Fuzzy membership	Land suitability modeling	Poland
Malins & Metternicht (2006)	Fuzzy membership	Soil salinization modeling	Australia
March et al. (2013)	Bayesian probability	Marine environmental modeling	Mediterranean Sea
Marquínez et al. (2003)	General probability theory	Rock-fall susceptibility modeling	Spain
Martin-Clouaire et al. (2000)	Possibility theory	Soil suitability modeling	France
Massei et al. (2014)	Rough set	Soil suitability modeling	Italy
Meinhardt et al. (2015)	General probability theory	Landslide susceptibility modeling	Vietnam
Metternicht & Gonzalez (2005)	Fuzzy rules	Natural hazard modeling	Bolivia
Metternicht (2001)	Fuzzy rules	Soil salinization modeling	Bolivia
Mihai et al. (2010)	Dempster–Shafer	Landslide susceptibility modeling	Romania
Mitra et al. (1998)	Fuzzy membership	Land suitability modeling	USA
Mogaji et al. (2015)	Dempster–Shafer	Groundwater resource modeling	Malaysia
Mohammadi et al. (2009)	Fuzzy classification	Groundwater resource modeling	Iran
Mohammadi et al. (2014)	General probability theory	Natural hazard modeling	Iran
Mohammady et al. (2012)	Dempster–Shafer	Landslide susceptibility modeling	Iran
Mosadeghi et al. (2015)	Fuzzy AHP	Urban planning and modeling	Australia
Mousavi et al. (2011)	General probability theory	Landslide susceptibility modeling	Iran
Mousavi et al. (2014)	General probability theory	Natural hazard modeling	Iran
Münch & Conrad (2007)	Probability map	Groundwater resource modeling	South Africa
Nachbaur & Rohmer (2011)	Fuzzy membership	Underground vulnerability modeling	France
Nampak et al. (2014)	Dempster–Shafer	Groundwater resource modeling	Malaysia
Nasserabadi et al. (2013)	Fuzzy membership	Land suitability modeling	Iran
Nath (2004)	General probability theory	Seismic hazard modeling	India
Navas et al. (2011)	Neuro fuzzy	Marine environmental modeling	Ireland
Navas et al. (2012)	Neuro fuzzy	Coastal modeling	Not available
Nelson et al. (2007)	Fuzzy membership	Landslide susceptibility modeling	Chile
Neshat & Pradhan (in press)	Dempster–Shafer	Groundwater resource modeling	Iran
Neshat et al. (2015)	General probability theory	Groundwater resource modeling	Iran
Neuhäuser et al. (2012)	General probability theory	Landslide susceptibility modeling	Austria
Nguyen et al. (2015)	Fuzzy membership	Land suitability modeling	Vietnam
Ning & Chang (2004)	Fuzzy multi-criteria analysis	Water quality modeling	Taiwan
Nisar Ahamed et al. (2000a)	Fuzzy membership	Land suitability modeling	India
Nisar Ahamed et al. (2000b)	Fuzzy membership	Soil suitability modeling	India
Nobre et al. (2007)	Fuzzy membership	Groundwater resource modeling	Brazil
Nourqolipour et al. (2015)	Fuzzy membership	Land use modeling	Malaysia
Nurmiaty (2014)	Fuzzy membership	Land suitability modeling	Indonesia
Ocalir et al. (2010)	Fuzzy membership	Site suitability modeling	Turkey
Ogburn (2006)	Fuzzy membership	Geo-historical modeling	Ecuador
Oh & Jeong (2002)	Fuzzy membership	Urban planning and modeling	Korea

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Text reference	Method	Application	Location
Oh & Lee (2011)	General probability theory	Landslide susceptibility modeling	Korea
Oh & Pradhan (2011)	Adaptive neuro-fuzzy inference system (ANFIS)	Landslide susceptibility modeling	Malaysia
Oh et al. (2011)	Frequency ratio	Ground subsidence modeling	Korea
Osna et al. (2014)	Mamdani's fuzzy inference modeling	Landslide susceptibility modeling	Turkey
Ozdemir (2009)	Bayesian probability	Landslide susceptibility modeling	Turkey
Park (2011)	Dempster–Shafer	Landslide susceptibility modeling	Korea
Park et al. (2012)	Adaptive neuro-fuzzy inference system (ANFIS)	Ground subsidence modeling	Korea
Park et al. (2013)	General probability theory	Landslide susceptibility modeling	Korea
Park et al. (2014)	Neuro fuzzy	Ground subsidence modeling	Korea
Parry et al. (2013)	General probability theory	Marine environmental modeling	Australia
Pászto et al. (2015)	Fuzzy membership	Urban planning and modeling	Czech Republic
Pathak & Hiratsuka (2011)	Fuzzy pattern recognition	Groundwater resource modeling	Nepal
Pawlin Vasanthi et al. (2015)	Probability map	Health risk modeling	India
Peled & Gilichinsky (2013)	General probability theory	Land use modeling	Israel
Peng (1998)	Bayesian probability	Soil salinization modeling	China
Peng et al. (2014)	Rough set	Landslide susceptibility modeling	China
Perakis & Moysiadis (2011)	Dempster–Shafer	Geo-historical modeling	Greece
Pezeshki et al. (2012)	Fuzzy classification	Health risk modeling	Iran
Plewe (2003)	Dempster–Shafer	Geo-historical modeling	Not available
Pollak (2014)	Bayesian probability	Urban planning and modeling	Israel
Pourghasemi et al. (2012)	Bayesian probability	Landslide susceptibility modeling	Iran
Pourghasemi et al. (2013a)	Dempster–Shafer	Landslide susceptibility modeling	Iran
Pourghasemi et al. (2013b)	General probability theory	Landslide susceptibility modeling	Iran
Pourghasemi et al. (2014a)	Dempster–Shafer	Landslide susceptibility modeling	Iran
Pourghasemi et al. (2014b)	General probability theory	Landslide susceptibility modeling	Iran
Pourtaghi & Pourghasemi (2014)	Bayesian probability	Groundwater resource modeling	Iran
Pradhan (2010)	Fuzzy membership	Landslide susceptibility modeling	Malaysia
Pradhan (2013)	Adaptive neuro-fuzzy inference system (ANFIS)	Landslide susceptibility modeling	Malaysia
Pradhan et al. (2009)	Fuzzy membership	Landslide susceptibility modeling	Malaysia
Pradhan et al. (2014)	Probability map	Ground subsidence modeling	Malaysia
Prasannakumar & Vijith (2012)	Probability map	Landslide susceptibility modeling	India
Qi et al. (2006)	Fuzzy membership	Soil suitability modeling	USA
Qi et al. (2013)	General probability theory	Flood management modeling	USA
Qiu et al. (2014)	Fuzzy membership	Land suitability modeling	USA
Rahman et al. (2014)	Fuzzy AHP	Environmental modeling	China
Rahman et al. (in press)	General probability theory	Soil erosion modeling	China
Ramani et al. (2011)	General probability theory	Landslide susceptibility modeling	India

Appendix B (*continued*)

Text reference	Method	Application	Location
Ramnarine et al. (2015)	General probability theory	Soil suitability modeling	USA
Razandi et al. (in press)	General probability theory	Earth Science Informatics	Iran
Refice & Capolongo (2002)	General probability theory	Landslide susceptibility modeling	Italy
Regmi et al. (2014)	Bayesian probability	Landslide susceptibility modeling	Nepal
Remondo et al. (2003)	Fuzzy membership	Landslide susceptibility modeling	Spain
Reshmidevi et al. (2009)	Fuzzy rules	Land suitability modeling	India
Robinson et al. (2004)	General probability theory	Mineral potential modeling	USA
Romanelli et al. (2012)	General probability theory	Landslide susceptibility modeling	Argentina
Romero-Calcerrada et al. (2008)	Bayesian probability	Human-caused wildfire modeling	Spain
Rüger et al. (2005)	Fuzzy membership	Habitat suitability modeling	Uzbekistan
Sadeghi & Khalajmasoumi (2015)	Fuzzy membership	Geothermal modeling	Azarbayejan
Saeidi (2014)	Dempster–Shafer	Land extraction modeling	Malaysia
Sahoo et al. (2015)	General probability theory	Groundwater resource modeling	India
Sakamoto & Fukui (2004)	Fuzzy AHP	Habitat suitability modeling	Japan
Samranpong et al. (2009)	Fuzzy membership	Land suitability modeling	Thailand
Schindler et al. (2012)	General probability theory	Natural hazard modeling	Germany
Schmidt & Hewitt (2004)	Fuzzy classification	Land suitability modeling	New Zealand
Schotten et al. (2001)	General probability theory	Land use modeling	Netherlands
Semple et al. (2013)	General probability theory	Health risk modeling	USA
Şener & Şener (2015)	Fuzzy AHP	Groundwater resource modeling	Turkey
Shad et al. (2009)	Fuzzy membership	Air pollution modeling	Iran
Shadman Roodposhti et al. (2014)	Fuzzy AHP	Landslide susceptibility modeling	Iran
Shahabi et al. (2015)	Fuzzy membership	Landslide susceptibility modeling	Iran
Shahid et al. (2002)	Fuzzy membership	Groundwater resource modeling	India
Sharma et al. (2013)	Fuzzy membership	Landslide susceptibility modeling	India
Sheng et al. (2012)	Rough set	Land use modeling	China
Shengyuan et al. (2008)	Fuzzy membership	Land suitability modeling	China
Shi et al. (2009)	Fuzzy C-means	Wind erosion modeling	Mongolia
Shi et al. (2013)	Fuzzy membership	Groundwater resource modeling	China
Shi et al. (2014)	Fuzzy membership	Natural hazard modeling	China
Shirzadi et al. (2012)	Probability map	Rock-fall susceptibility modeling	Iran
Sicat et al. (2005)	Fuzzy multi-criteria analysis	Land suitability modeling	India
Simav et al. (2013)	General probability theory	Coastal modeling	Turkey
Široký et al. (2011)	Probability map	Health risk modeling	Czech Republic
Skov & Svenning (2003)	Fuzzy cognitive modeling	Soil suitability modeling	Denmark
Solaimani et al. (2013)	Dempster–Shafer	Landslide susceptibility modeling	Iran
Soltani et al. (2013)	Dempster–Shafer	Land use modeling	Iran
Soto et al. (2012)	Fuzzy membership	Natural hazard modeling	Chile
Steinhardt (1998)	Fuzzy membership	Land use modeling	Germany
Stoms et al. (2002)	Fuzzy membership	Land suitability modeling	USA

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Text reference	Method	Application	Location
Subburayalu et al. (2014)	Possibility theory	Soil suitability modeling	USA
Sujatha & Rajamanickam (2011)	Fuzzy membership	Landslide susceptibility modeling	India
Sun et al. (2014)	Fuzzy membership	Natural hazard modeling	China
Sutcu et al. (2012)	General probability theory	Mineral resources modeling	Turkey
Svoray et al. (2004)	Fuzzy rules	Land suitability modeling	Israel
Taboada et al. (2008)	Fuzzy AHP	Mineral potential modeling	Spain
Talaei (2014)	General probability theory	Landslide susceptibility modeling	Iran
Tang & Zhu (2006)	General probability theory	Torrent risk modeling	China
Tang et al. (2012)	Fuzzy membership	Environmental modeling	USA
Tang et al. (2013)	Bayesian probability	Fishing grounds modeling	North Pacific
Tangestani & Moore (2002)	Dempster–Shafer	Mineral potential modeling	Iran
Tangestani & Moore (2003)	Fuzzy membership	Mineral potential modeling	Iran
Tangestani (2009)	Dempster–Shafer	Landslide susceptibility modeling	Iran
Thiam (2005)	Dempster–Shafer	Land degradation modeling	Mauritania
Tripathi et al. (2015)	Fuzzy C-means	Soil suitability modeling	India
Tsutsumida et al. (2015)	General probability theory	Urban planning and modeling	Mongolia
Tucker et al. (1997)	Bayesian probability	Bird distribution modeling	United Kingdom
Uddameri & Honnungar (2007)	Rough set	Groundwater resource modeling	USA
Urbański & Szymelfenig (2003)	Fuzzy membership	Benthic habitat modeling	Poland
Vadrevu et al. (2010)	Fuzzy membership	Natural hazard modeling	India
Vafai et al. (2013)	Fuzzy multi-criteria analysis	Marine environmental modeling	Iran
Vahidnia et al. (2009)	Fuzzy AHP	Land suitability modeling	Iran
Vakalis et al. (2004)	Neuro fuzzy	Natural hazard modeling	Greece
Venkataraman et al. (2000)	Fuzzy membership	Mineral potential modeling	India
Venkatramanan et al. (in press)	Fuzzy AHP	Groundwater resource modeling	Korea
Verbeeck et al. (2011)	Transition probability	Urban planning and modeling	France
Vijith & Madhu (2008)	Frequency ratio	Landslide susceptibility modeling	India
Vijith et al. (2012)	General probability theory	Landslide susceptibility modeling	India
Wan et al. (2008)	Rough set	Debris flows moldeing	Taiwan
Wan et al. (2010)	Rough set	Landslide susceptibility modeling	Taiwan
Wan et al. (2012)	Rough set	Landslide susceptibility modeling	Taiwan
Wang et al. (2009)	Fuzzy membership	Landslide susceptibility modeling	China
Wang et al. (2012)	Fuzzy cellular automata	Urban planning and modeling	China
Wang et al. (2013)	Neuro fuzzy	Reservoir characterization	Canada
Weissteiner et al. (2011)	Fuzzy membership	Land suitability modeling	Mediterranean
Wikramanayake et al. (2004)	General probability theory	Wilderness land modeling	India and Nepal
Wiley et al. (2011)	General probability theory	Marine environmental modeling	USA
Wood & Dragicevic (2007)	Fuzzy membership	Marine environmental modeling	Canada
Wu et al. (1998)	Fuzzy membership	Land use modeling	China
Wu et al. (2012)	Transition probability	Land use modeling	China

Appendix B (*continued*)

Text reference	Method	Application	Location
Wu et al. (2013)	Rough set	Landslide susceptibility modeling	China
Xia & Chen (2015)	Fuzzy membership	Water quality modeling	China
Xie et al. (2004)	Probability map	Landslide susceptibility modeling	Japan
Xu (2001)	General probability theory	Landslide susceptibility modeling	Hong Kong
Yalcin et al. (2011)	Frequency ratio	Landslide susceptibility modeling	Turkey
Yang & Yang (2005)	Dempster–Shafer	Soil salinization modeling	China
Yang et al. (2005)	Dempster–Shafer	Soil salinization modeling	China
Yang et al. (2008)	Gray relational analysis	Land suitability modeling	China
Yang et al. (2014a)	Fuzzy membership	Nature conservation modeling	China
Yang et al. (2014b)	Fuzzy AHP	Soil suitability modeling	China
Yi et al. (2010)	General probability theory	Natural hazard modeling	Korea
Yigit (2012)	General probability theory	Mineral potential modeling	Turkey
Yilmaz et al. (2013)	Bayesian probability	Natural hazard modeling	Turkey
Youssef et al. (in press-a)	Dempster–Shafer	Landslide susceptibility modeling	Saudi Arabia
Youssef et al. (in press-b)	General probability theory	Landslide susceptibility modeling	Saudi Arabia
Zahiri et al. (2006)	General probability theory	Mineral potential modeling	Australia
Zamorano et al. (2008)	General probability theory	Land suitability modeling	Spain
Zeller at al. (2011)	General probability theory	Wilderness land modeling	Nicaragua
Zeng & Zhou (2001)	Fuzzy rules	Urban planning and modeling	Australia
Zhang & Guilbert (2013)	Fuzzy membership	Groundwater resource modeling	Russia
Zhang et al. (2004)	Fuzzy AHP	Soil suitability modeling	China
Zhang et al. (2009)	Fuzzy AHP	Land suitability modeling	China
Zhang et al. (2010)	General probability theory	Natural hazard modeling	China
Zhang et al. (2013a)	Fuzzy AHP	Land suitability modeling	China
Zhang et al. (2013b)	Fuzzy membership	Urban planning and modeling	China
Zhang et al. (2014)	Fuzzy multi-criteria analysis	Urban planning and modeling	Finland
Zhang et al. (2015)	Fuzzy AHP	Land suitability modeling	China
Zhijun et al. (2009)	General probability theory	Natural hazard modeling	China
Zhou et al. (1997)	Fuzzy AHP	Land suitability modeling	Thailand
Zhou et al. (2003)	General probability theory	Landslide susceptibility modeling	Japan
Zhu & Mackay (2001)	Fuzzy membership	Hydro-ecological modeling	USA
Zhu et al. (1996)	Fuzzy membership	Soil suitability modeling	USA
Zhu et al. (2006)	Rough set	Soil suitability modeling	China
Zhu et al. (2014)	Fuzzy membership	Landslide susceptibility modeling	China
Zou et al. (2013)	Fuzzy AHP	Natural hazard modeling	China

References

[1] O. Ahlqvist, J. Keukelaar, K. Oukbir, Rough classification and accuracy assessment, Int. J. Geogr. Inf. Sci. 14 (5) (2000) 475–496.
[2] P. Baofu, The Future of Post-Human Meta-Data: Towards a New Theory of Structure and Process in Information Science, Primrose Hall Publishing Group, Brisbane, Australia, 2015.
[3] T. Beaubouef, F. Petry, J. Breckenridge, Rough set based uncertainty management for spatial databases and geographical information systems, in: Y. Suzuki (Ed.), Soft Computing in Industrial Applications, Springer-Verlag, London, UK, 2000, pp. 471–479.
[4] J.J. Becker, D.T. Sandwell, W.H.F. Smith, J. Braud, B. Binder, J. Depner, D. Fabre, J. Factor, S. Ingalls, S.-K. Kim, R. Ladner, K. Marks, S. Nelson, A. Pharaoh, R. Trimmer, J. Von Rosenberg, G. Wallace, P. Weatherall, Global bathymetry and elevation data at 30 arc seconds resolution: SRTM30_PLUS, Mar. Geodesy 32 (4) (2009) 355–371.
[5] S. Benferhat, D. Dubois, H. Prade, From semantic to syntactic approach to information combination in possibilistic logic, in: B. Bouchon-Meunier (Ed.), Aggregation and Fusion of Imperfect Information, Physica-Verlag, Heidelberg, Germany, 1997, pp. 141–151.
[6] E. Binaghi, L. Luzi, P. Madella, F. Pergalani, A. Rampini, Slope instability zonation: a comparison between certainty factor and fuzzy Dempster–Shafer approaches, Nat. Hazards 17 (1998) 77–97.
[7] T. Bittner, J. Stell, Stratified rough sets and vagueness, in: W. Kuhn, M.F. Worboys, S. Timpf (Eds.), COSIT 2003, LNCS, vol. 2825, Springer, Berlin, Heidelberg, 2003, pp. 286–303.
[8] J. Chacón, C. Irigaray, R. El Hamdouni, T. Fernández, Engineering geology maps: landslides and geographical information systems, Bull. Eng. Geol. Environ. 65 (4) (2006) 341–411.
[9] M. Cobb, F. Petry, Modeling spatial data within a fuzzy framework, J. Am. Soc. Inf. Sci. 49 (3) (1998) 253–266.
[10] H. Couclelis, The certainty of uncertainty: GIS and the limits of geographic knowledge, Trans. GIS 7 (2) (2003) 165–175.
[11] V. Cross, A. Firat, Fuzzy objects for geographical information systems, Fuzzy Sets Syst. 113 (2000) 19–36.
[12] G. De Tré, R. De Caluwe, A generalized object-oriented database model with generalized constraints, in: Proceedings NAFIPS 1999, New York, NY, 1999, pp. 381–386.
[13] A.P. Dempster, Upper and lower probabilities induced by a multivalued mapping, Ann. Math. Stat. 38 (2) (1967) 325–339.
[14] D. Dubois, H. Prade, Representation and combination of uncertainty with belief functions and possibility measures, Comput. Intell. 4 (1988) 244–264.
[15] D. Dubois, W. Liu, J. Ma, H. Prade, Towards a general framework for information fusion, in: The 10th International Conference on Modeling Decisions for Artificial Intelligence (MDAI'13), Barcelona, Spain, 2013, pp. 37–48.
[16] A.M. Ellison, Bayesian inference in ecology, Ecol. Lett. 7 (2004) 509–520.
[17] P. Fisher, Boolean and fuzzy regions, in: P.A. Burrough, A. Frank (Eds.), Geographic Objects with Indeterminate Boundaries, Taylor and Francis Publishing, London, UK, 1996, pp. 87–94.
[18] S. Gale, Inexactness, fuzzy sets, and the foundations of behavioral geography, Geogra. Anal. 4 (1972) 337–349.
[19] J.Y. Halpern, R. Fagin, Two views of belief: belief as generalized probability and belief as evidence, Artif. Intell. 54 (1992) 275–317.
[20] A. Jousselme, P. Maupin, Distances in evidence theory: comprehensive survey and generalizations, Int. J. Approx. Reason. 53 (2) (2012) 118–145.
[21] W. Liu, Analyzing the degree of conflict among belief functions, Artif. Intell. 170 (11) (2006) 909–924.
[22] W. Liu, J.G. Hughes, M.F. McTear, Representing heuristic knowledge in the DS theory, in: Proceedings of the Eighth Conference on Uncertainty in Artificial Intelligence (UAI'92), Stanford University, Morgan Kaufman, CA, 1992, pp. 182–190.
[23] J.D. Lowrance, T.D. Garvey, T. Strat, 1996. A framework for evidential-reasoning systems, in: Proceedings of AAAI Conference, pp. 896–903.
[24] J. Malczewski, GIS-based multicriteria decision analysis: a survey of the literature, Int. J. Geogr. Inf. Sci. 20 (7) (2006) 703–726.
[25] J.A. Malpica, M.C. Alonso, M.A. Sanz, Dempster–Shafer theory in geographic information systems: a survey, Expert Syst. Appl. 32 (1) (2007) 47–55.
[26] D.F. Marble, Geographic information systems: an overview, in: Proceedings of the Pecora 9 Conference, Sioux Falls, SD, 1984, pp. 18–24.
[27] A. Morris, A framework for modeling uncertainty in spatial databases, Trans. GIS 7 (2006) 83–101.
[28] Z. Pawlak, Rough sets, Int. J. Man Mach. Stud. 21 (1984) 127–134.
[29] W. Pedrycz, F. Gomide, An Introduction to Fuzzy Sets: Analysis and Design, MIT Press, Boston, MA, 1996.
[30] S. Rahimi, M. Cobb, A. Dia, F. Petry, A knowledge-based multi-agent system for geospatial data conflation, J. Geogr. Inf. Decis. Anal. 2 (5) (2002) 67–81.
[31] V. Robinson, A. Frank, About different kinds of uncertainty in geographic information systems, in: Proceedings AUTOCARTO 7 Conference, American Society for Photogrammetry and Remote Sensing, Falls Church, VA, 1985, pp. 440–449.
[32] T.L. Saaty, The Analytic Hierarchy Process, McGraw-Hill International, New York, NY, 1980.
[33] T.L. Saaty, Fundamentals of Decision Making and Priority Theory with the AHP, RWS Publications, Pittsburgh, PA, 1994.
[34] M. Schneider, Spatial Data Types for Database Systems (Doctoral Thesis), FernUniversität, Hagen, Germany, 1995.
[35] G. Shafer, A Mathematical Theory of Evidence, Princeton University Press, Princeton, NJ, 1976.
[36] P. Smets, Belief functions: the disjunctive rule of combination and the generalized Bayesian theorem, Int. J. Approx. Reason. 9 (1) (1993) 1–35.
[37] P. Smets, Decision making in the TBM: the necessity of the pignistic transformation, Int. J. Approx. Reason. 38 (2) (2004) 133–147.
[38] L. Strat, Evidential-based control in knowledge-based systems (Ph.D. Dissertation), University of Massachusetts, 1987.
[39] L. Uusitalo, Advantages and challenges of Bayesian networks in environmental modelling, Ecol. Model. 203 (3–4) (2007) 312–318.
[40] A.C. Varsi, Philosophical issues in geography – an introduction, Topoi 20 (2001) 119–130.
[41] A.C. Varsi, Vagueness in geography, Philos. Geogr. 4 (2001) 49–65.
[42] F. Wang, A fuzzy grammar and possibility theory-based natural language user interface for spatial queries, Fuzzy Sets Syst. 113 (2000) 147–159.
[43] S. Wang, H. Yuan, G. Chen, D. Li, W. Shi, Rough Spatial Interpretation, in: S. Tsumoto, R. Słowiński, J. Komorowski, J.W. Grzymała-Busse (Eds.), RSCTC 2004, LNCS (LNAI), vol. 3066, Springer, Berlin, Heidelberg, 2004, pp. 435–444.
[44] M. Worboys, Imprecision in finite resolution spatial data, Geoinformatica 2 (3) (1998) 257–280.
[45] R.R. Yager, On the Dempster–Shafer framework and new combination rules, Inf. Sci. 41 (2) (1987) 93–137.
[46] R.R. Yager, M. Fedrizzi, J. Kacprzyk (Eds.), Advanced in the Dempster–Shafer Theory of Evidence, John Wiley and Sons, New York, NY, 1994.
[47] J. Yen, R. Langari, Fuzzy Logic: Intelligence, Control, and Information, Prentice Hall, Upper Saddle River, NJ, 1999.
[48] L. Zadeh, Fuzzy sets as a basis for a theory of possibility, Fuzzy Sets Syst. 1 (1978) 3–28.
[49] L. Zadeh, Fuzzy sets, Inf. Control 8 (1965) 338–353.
[50] L.A. Zadeh, A simple view of the Dempster–Shafer theory of evidence and its implication for the rule of combination, AI Mag. 7 (2) (1986) 85–90.
[51] J. Zhang, M. Goodchild, Uncertainty in Geographical Information, Taylor and Francis Publishing, London, UK, 2002.